Color vision: from pixels to objects

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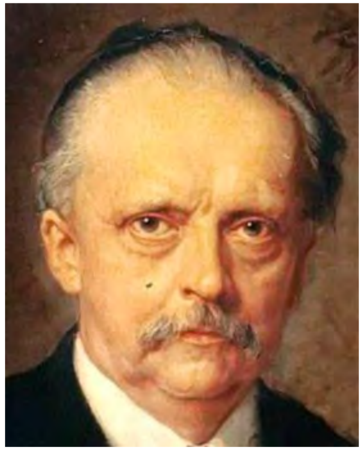
Justus-Liebig-Universität Giessen

erc Advanced Grant Color 3.0

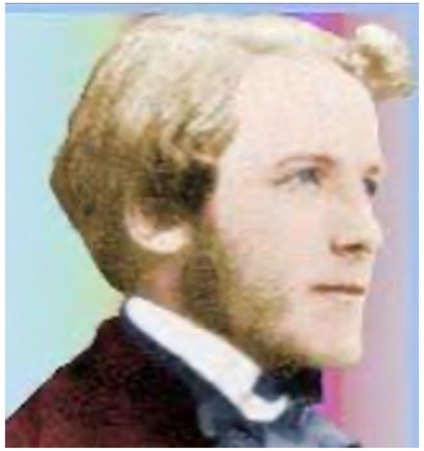
Cardinal Mechanisms of Perception

DFG Deutsche Forschungsgemeinschaft

Origins of color vision

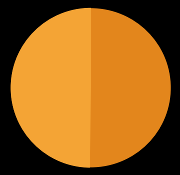


Hermann von Helmholtz
1821 - 1894

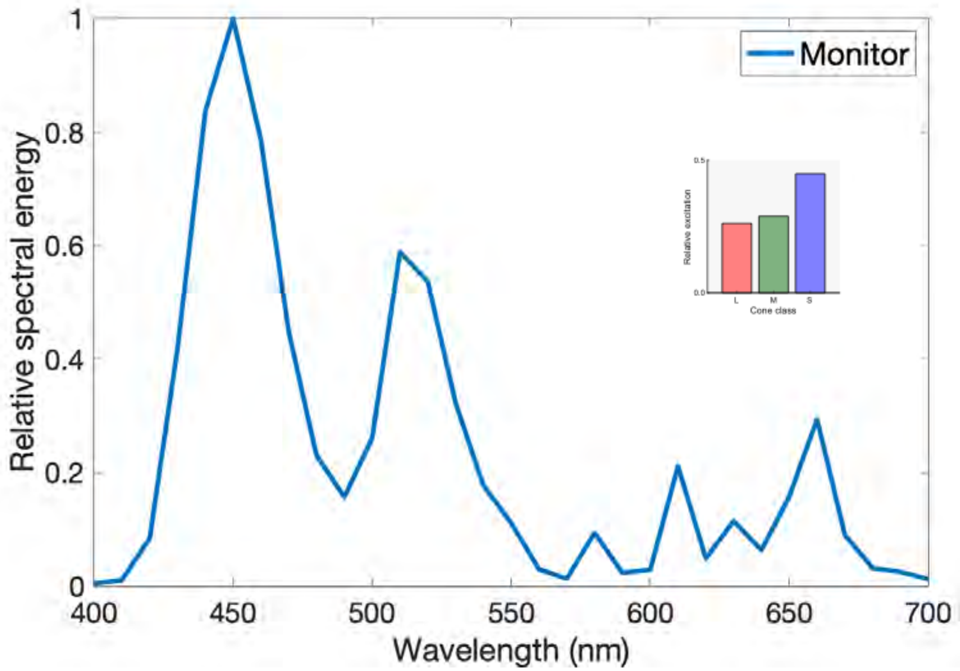


James Clerk Maxwell
1831 - 1879

Thomas Young
1773 - 1829



Das Mädchen mit dem Perlenohrgehänge
(niederländisch: *Meisje met de parel*)
Jan Vermeer (1632-1675).



Mauritshuis

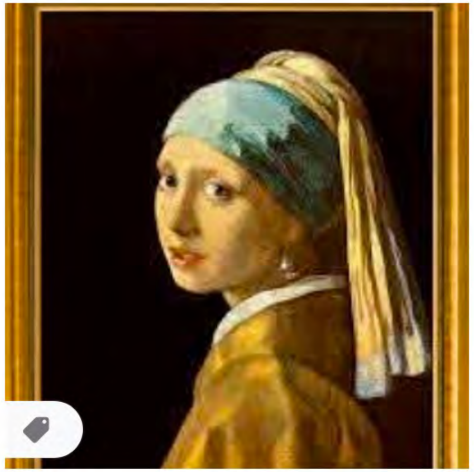
Mauritshuis
Den Haag, Netherlands

Google

vermeer mädchen perlenohrring

Leinwand (60x80cm): Ja...
amazon.de

Das Mädchen mit dem Perlen...
de.wikipedia.org



Jan Vermeer van Delft: Bild "...
arsmundi.de · In stock

dem Perlenohrring Poste...
posterlounge.de · In stock

dem Perlenohrring ...
mondialart.eu · In stock

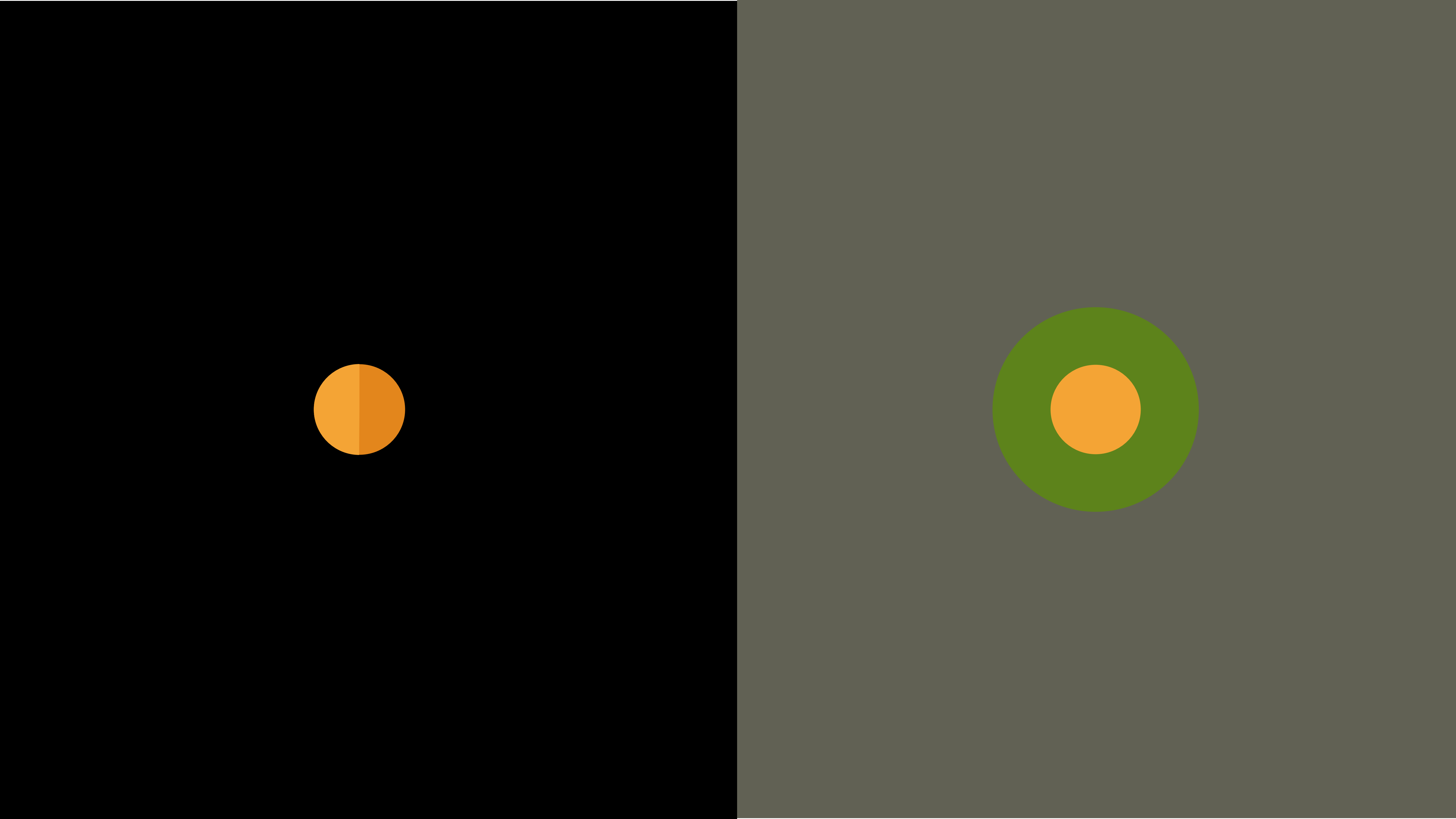
EUROGRAPHICS Puzzl...
puzzle.de

Holland.com
holland.com

Das Mädchen mit dem Per...
ebay.de · In stock

Johannes vermeer ...
pinterest.de

Bild - Druck AUF LEINW...
amazon.de



Gegenfurtner & Kiper, Annual Review of Neuroscience, 2003

Why Color?

What is Color Good For?

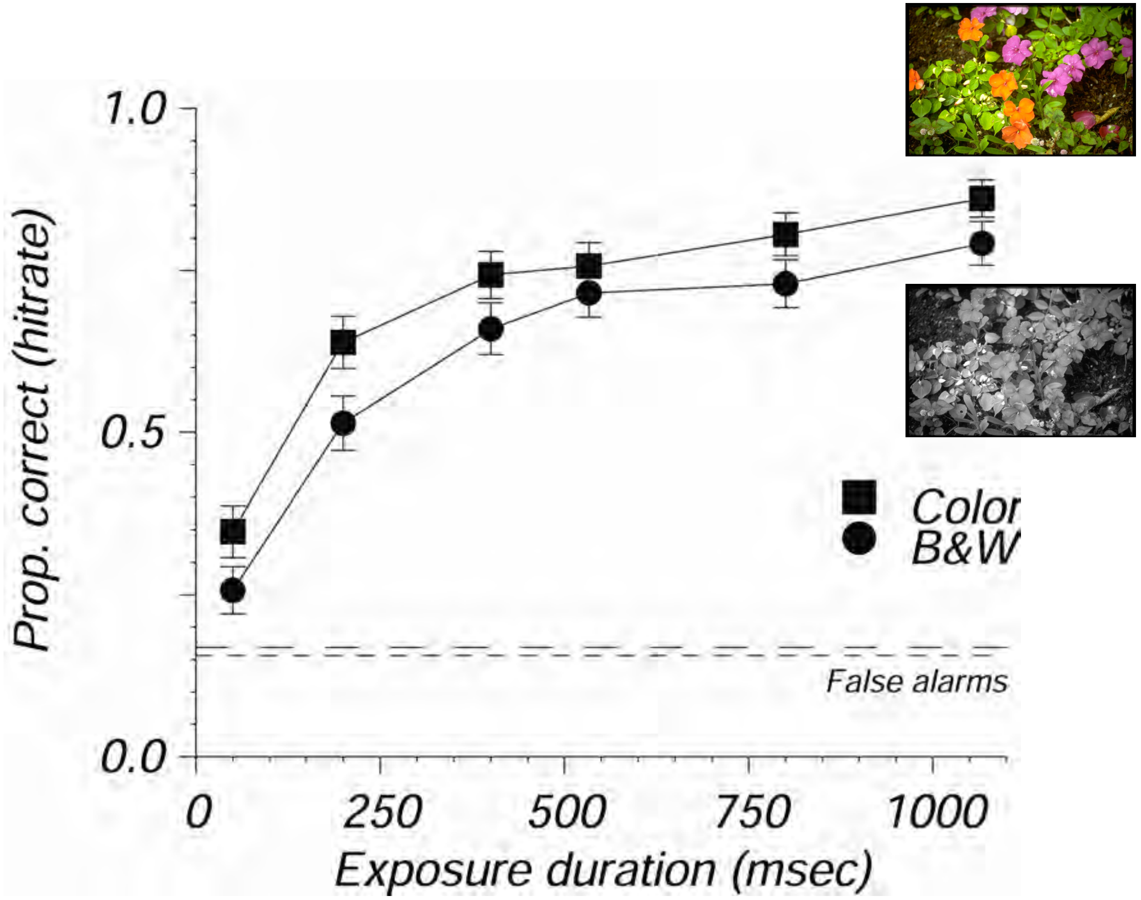
It‘s All About Hue

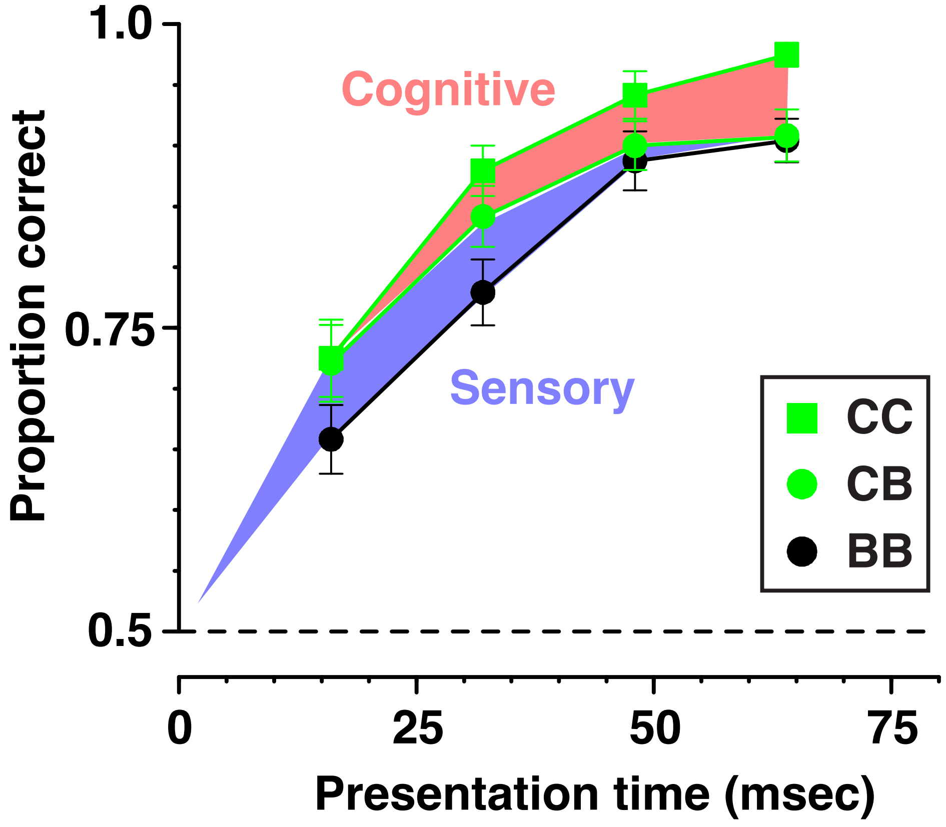
Color & Objects: Chromatic Edges

Color & Objects: Color Constancy

Gegenfurtner & Kiper, Annual Review of Neuroscience, 2003

Color helps to see things quicker and to remember them better





Wichmann, Sharpe & Gegenfurtner, JEP: LM&C, 2002

Gegenfurtner & Rieger, Current Biology, 2000

Why Color?

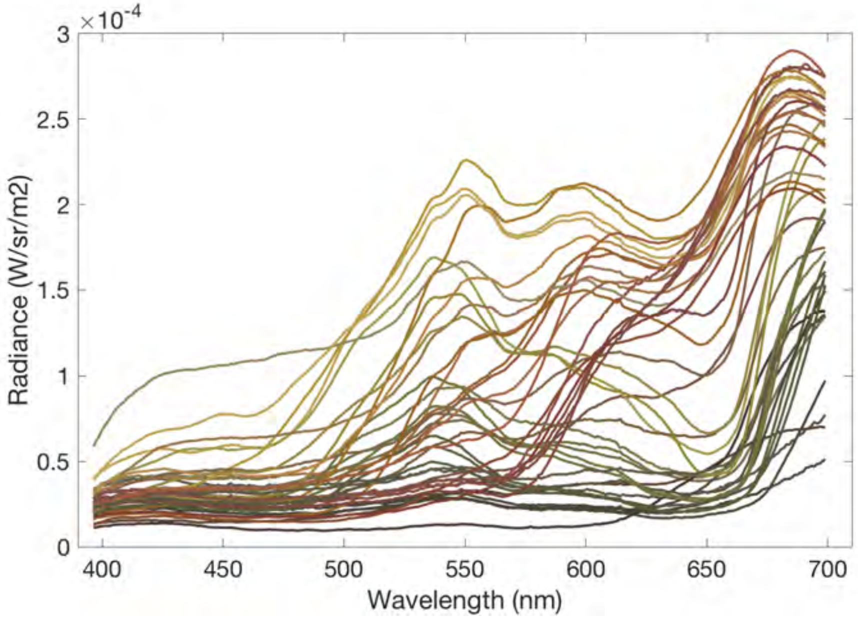
What is Color Good For?

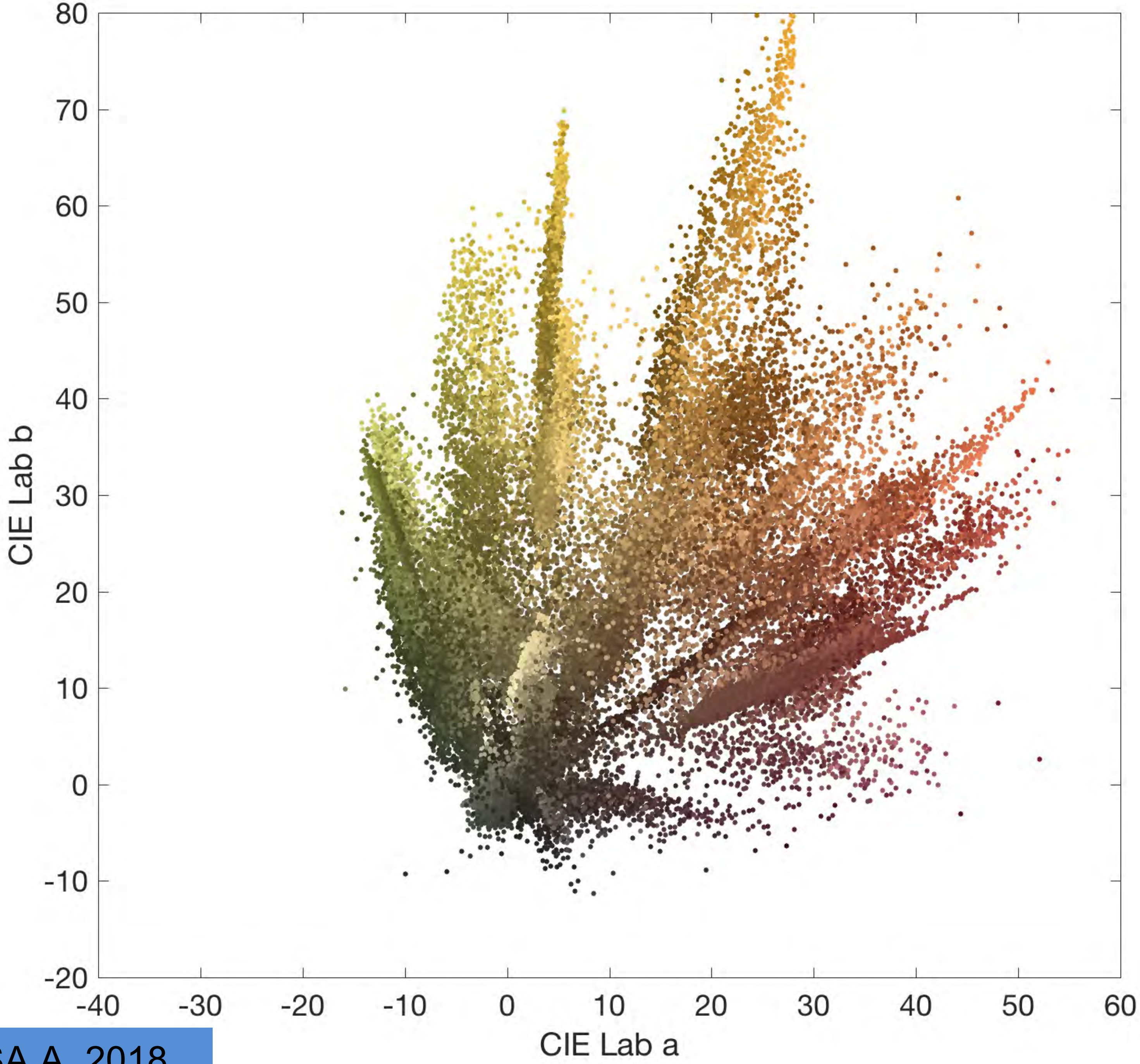
It‘s All About Hue

Color & Objects: Chromatic Edges

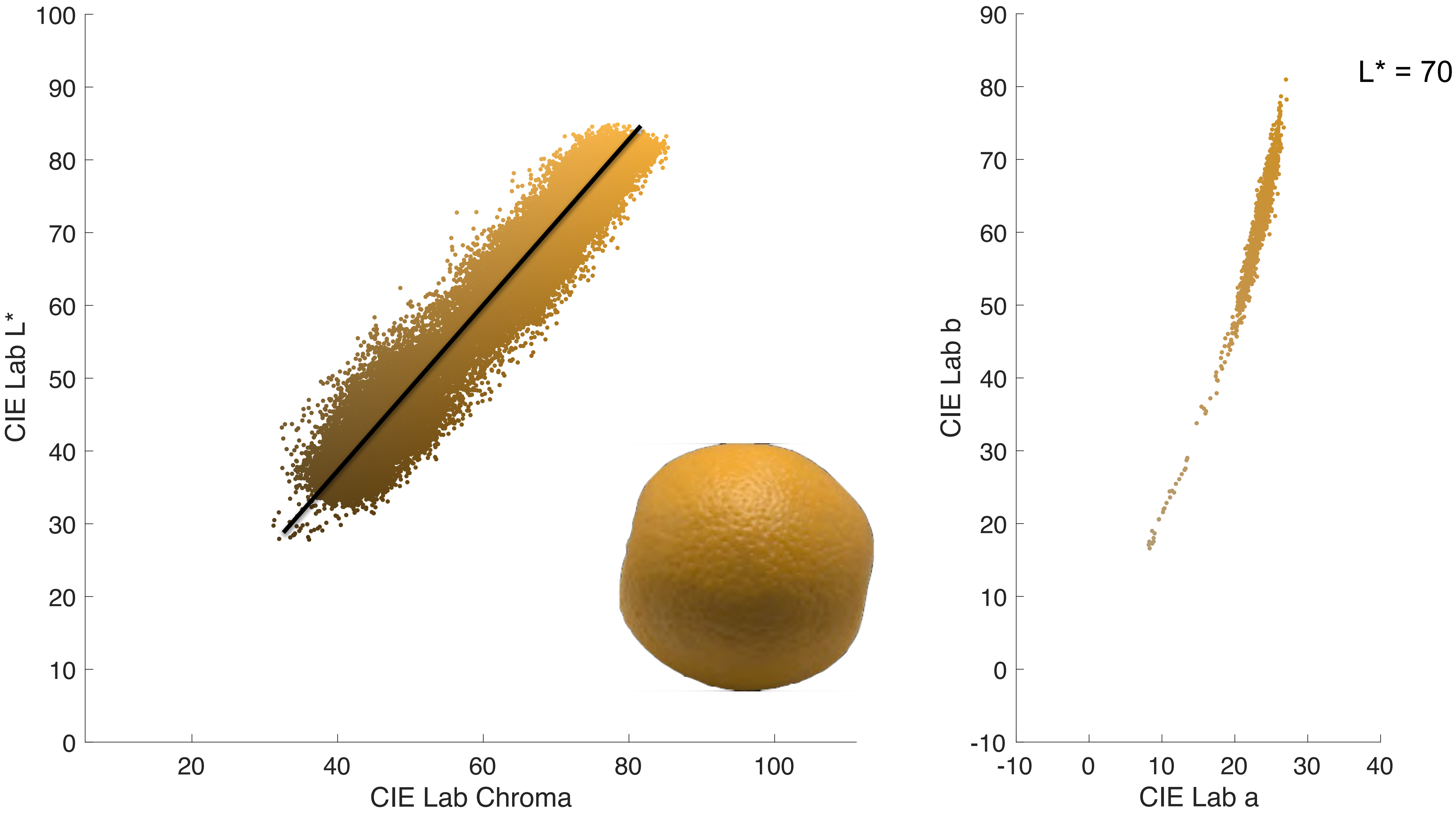
Color & Objects: Color Constancy

What‘s Next?

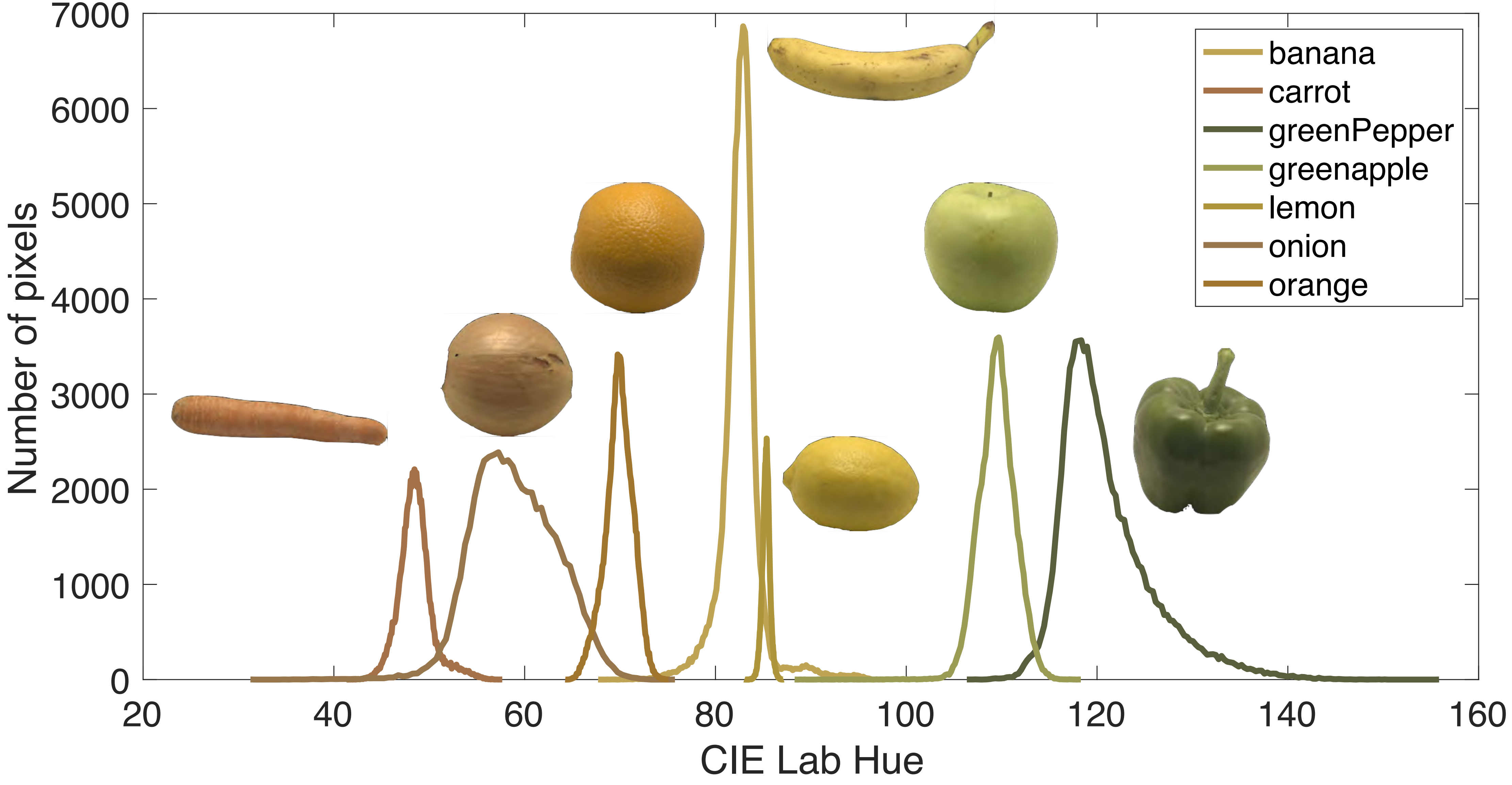




Ennis, Schiller, Toscani & Gegenfurtner, JOSA A, 2018


100
90
80
70
60
50
40
30
20
10
0
CIE Lab L*
20
40
60
80
100
CIE Lab Chroma
L* = 70
90
80
70
60
50
40
30
20
10
0
-10
CIE Lab b
-10
0
10
20
30
40
CIE Lab a

Hue distributions



Vision Res. Vol. 32, No. 11, pp. 2165–2175, 1992
Printed in Great Britain.

0042-6989/92 $5.00 + 0.00

Color Discrimination and Adaptation

JOHN KRAUSKOPF,* KARL GEGENFURTNER*

Received 22 April 1991; in revised form 16 January 1992

PROCEEDINGS B

rspb.royalsocietypublishing.org

Research

Superior discrimination for hue than for saturation and an explanation in terms of correlated neural noise

M. V. Danilova[1,2] and J. D. Mollon[2]

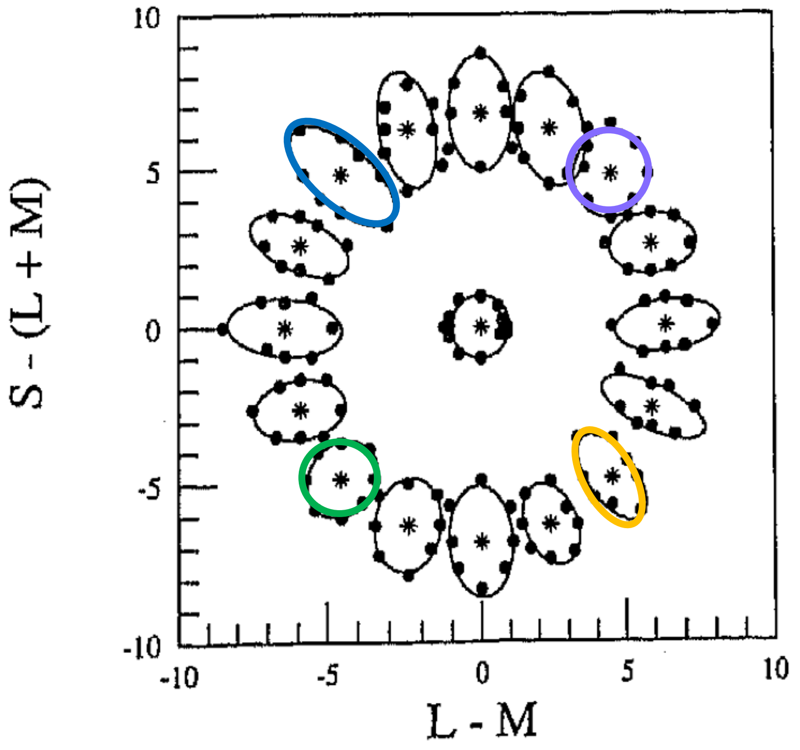


FIGURE 14. Discrimination ellipses for test vectors equally spaced in 16 directions around the white point. The adaptation point was white.

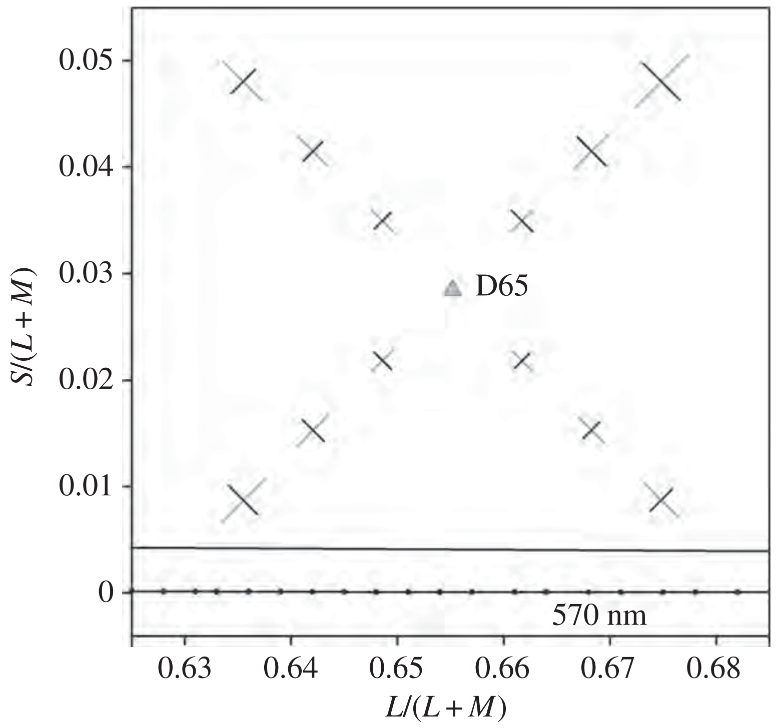
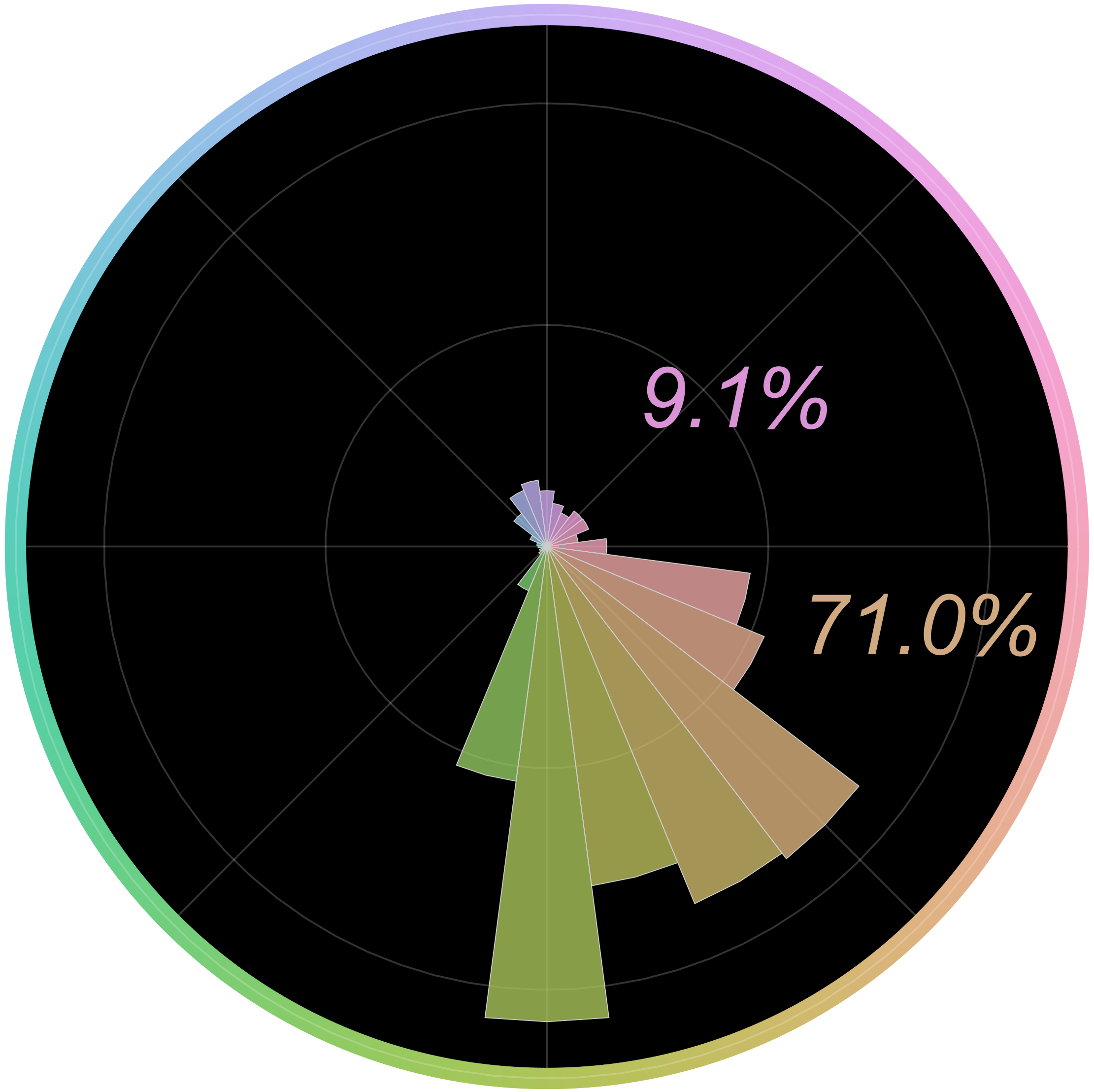


Figure 3. Average results for five observers, plotted in the MacLeod–Boynton diagram. The dashes directly show the separation of targets and distractors at threshold. D65 indicates the chromaticity of the neutral adapting field. The dotted line indicates part of the spectrum locus.

Hue histogram - 6,476 natural objects' reflectances

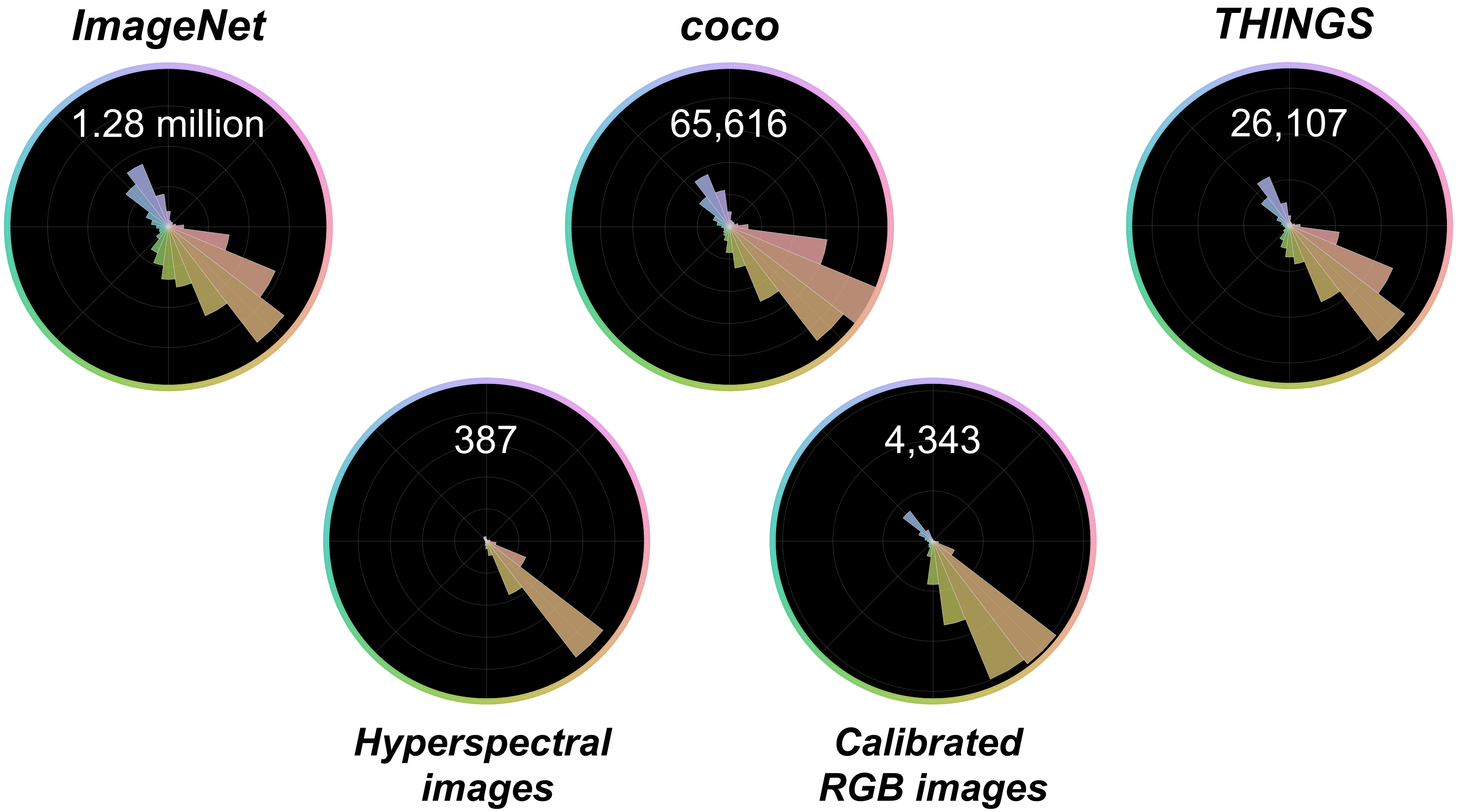


■ Sampled from 7 databases

(Barnard, Brown, Cambridge, Fred, Krinov, Matsumoto and Morimoto)

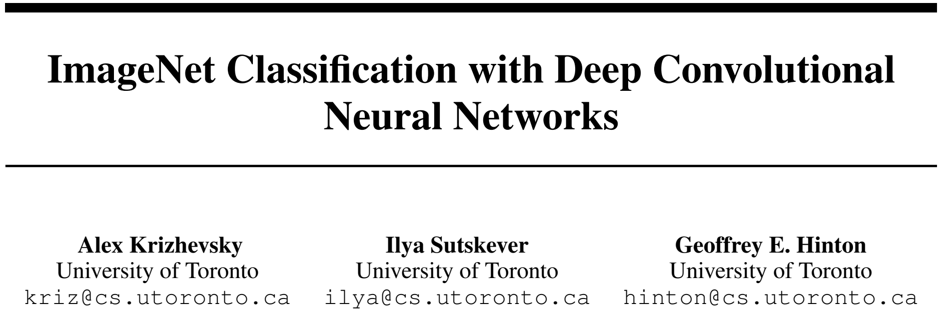
■ Object categories

bark, flowers, fruits, grass, human skin and hair, leaves, lichen, pelage, plants, rocks, stone, snow, soil, tree logs, vegetable, vegetation etc..

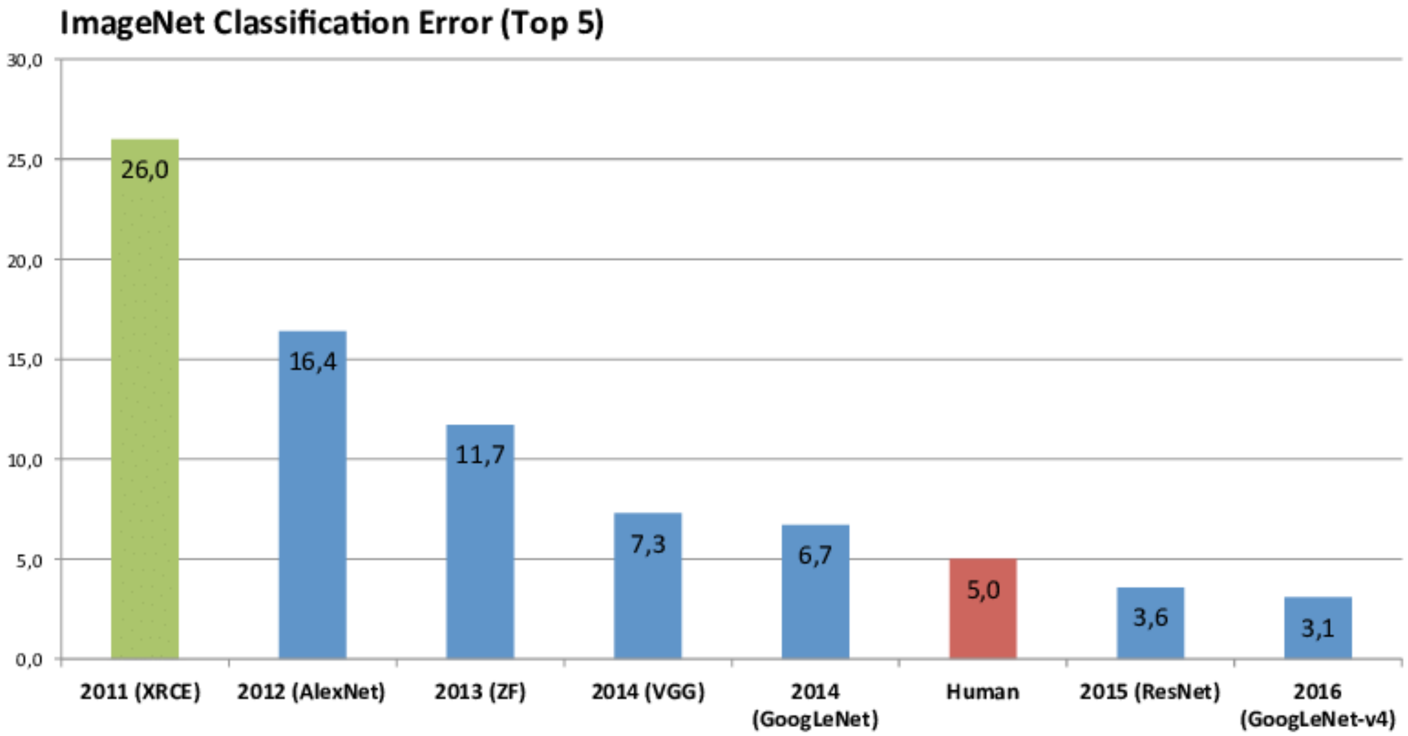


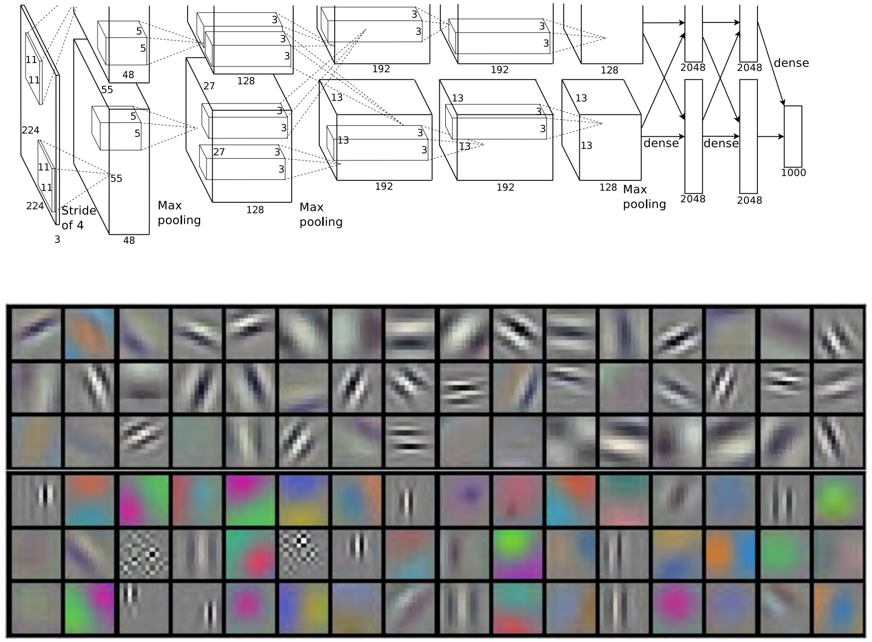
Takuma Morimoto, Arash Akbarinia, Laysa Hedjar, Shuchen Guan, Matteo Toscani, and Karl Gegenfurtner: Spontaneous Emergence of Asymmetries in Chromatic Discrimination From Deep Neural Networks Trained on Real-World Colour Images. In preparation.

Deep Neural Networks

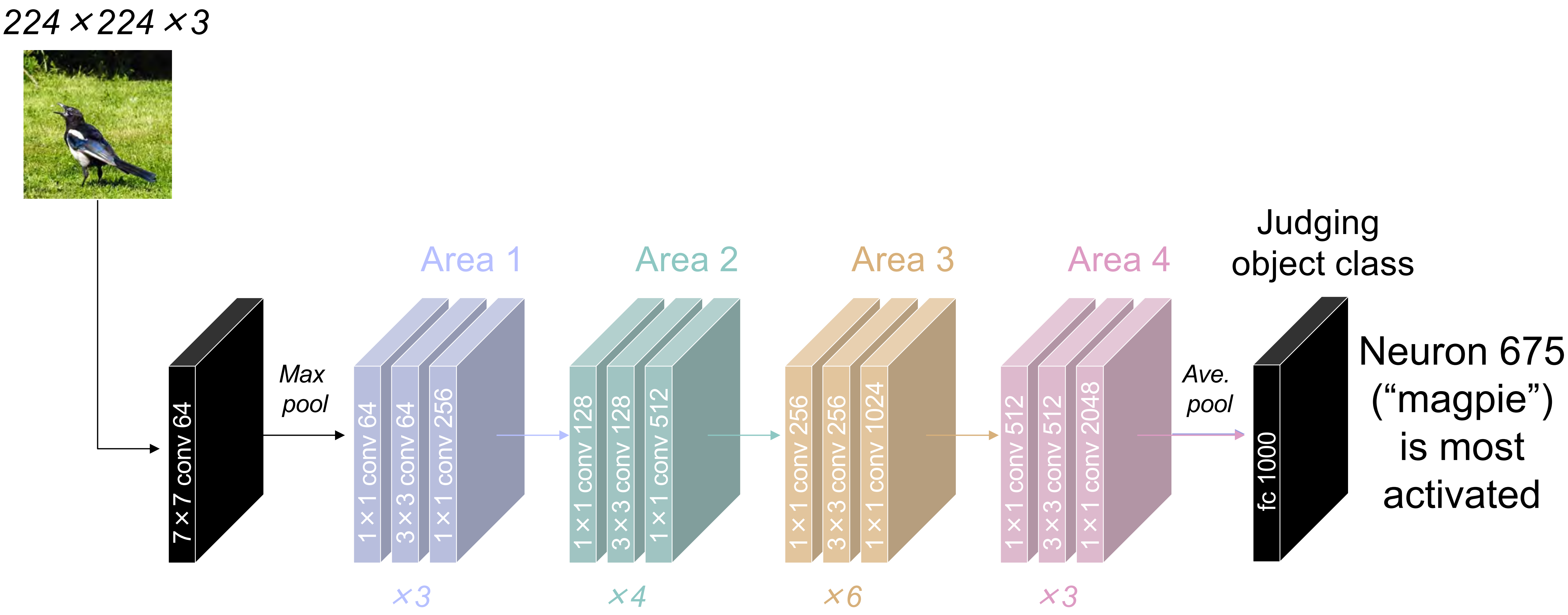


NIPS 2012

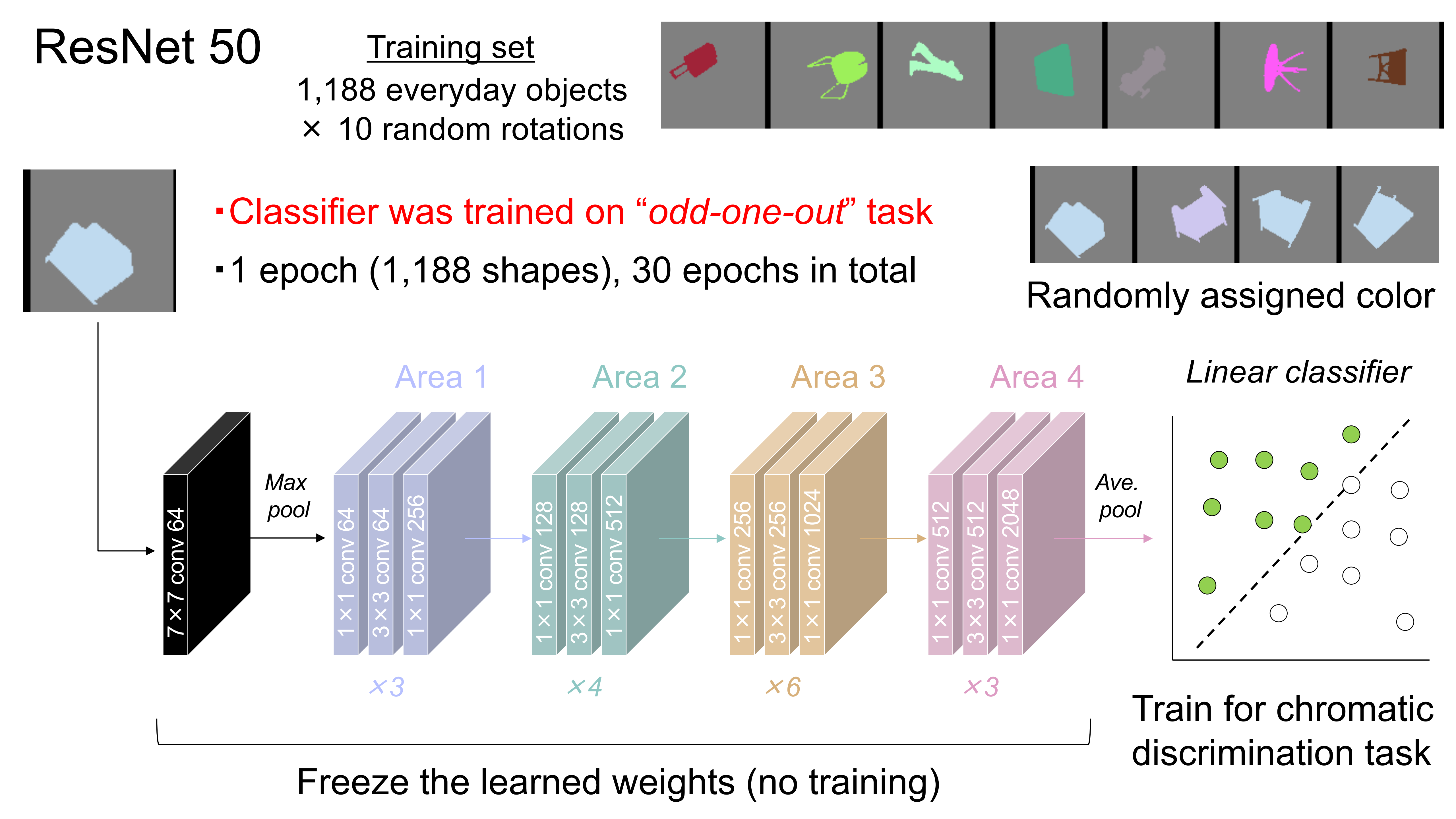


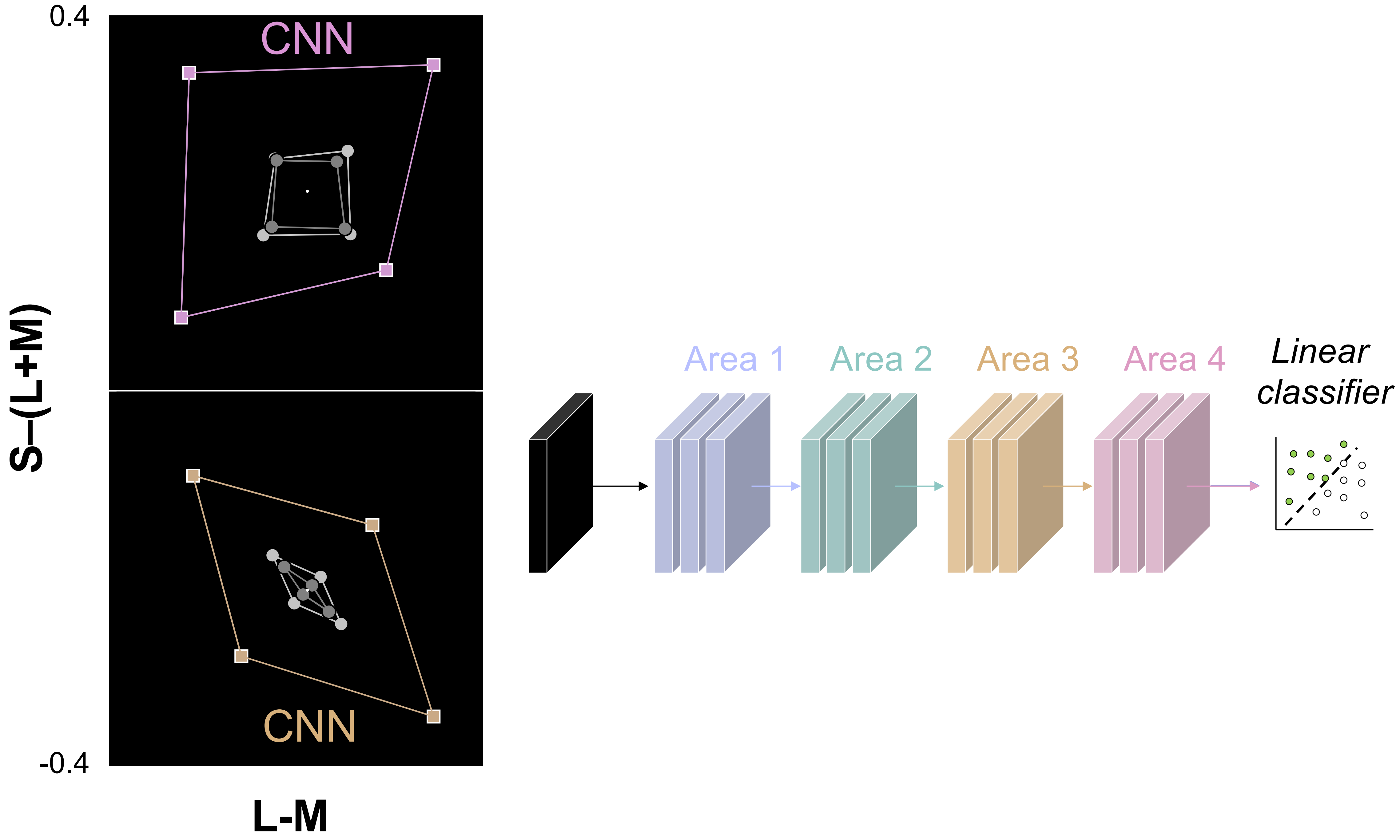


ResNet 50

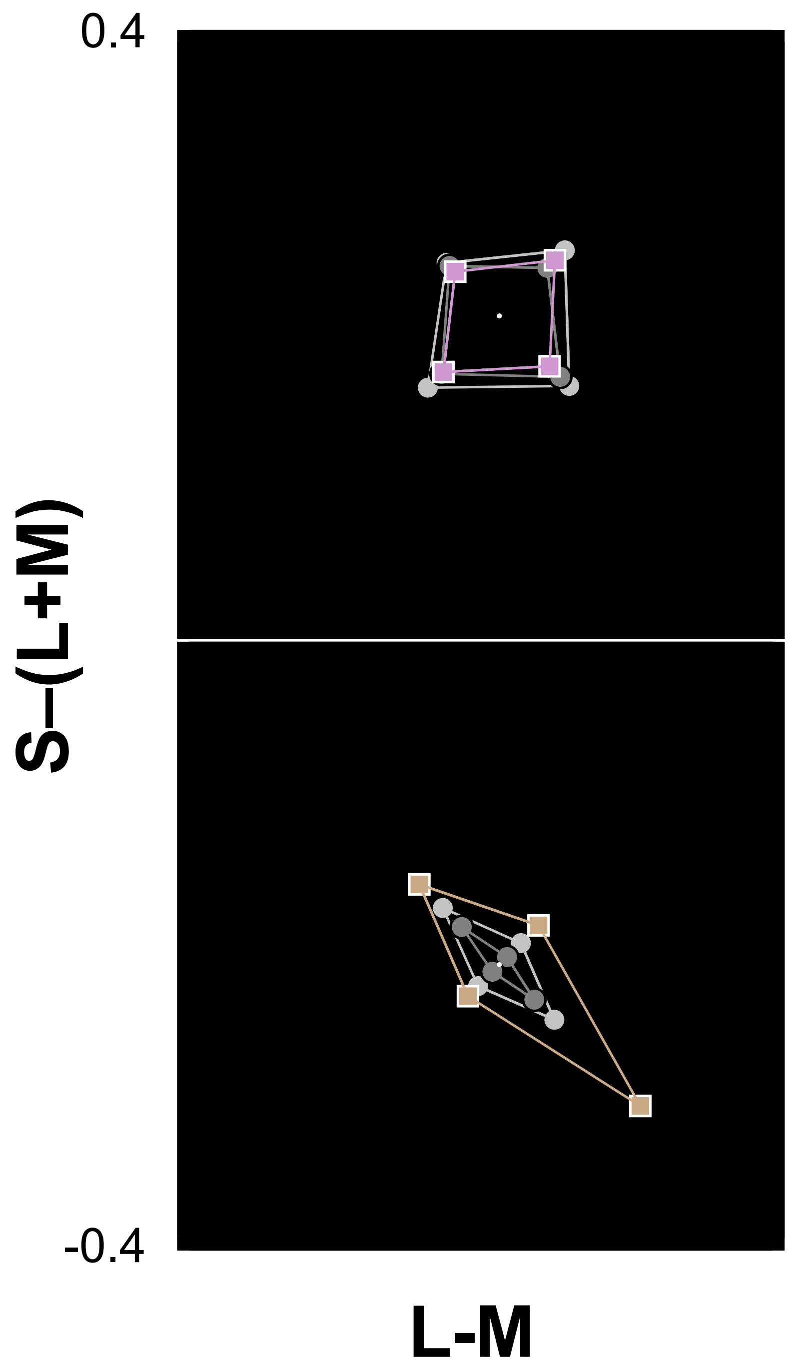


224 × 224 × 3
7 × 7 conv 64
Max pool
Area 1
1 × 1 conv 64
3 × 3 conv 64
1 × 1 conv 256
×3
Area 2
1 × 1 conv 128
3 × 3 conv 128
1 × 1 conv 512
×4
Area 3
1 × 1 conv 256
3 × 3 conv 256
1 × 1 conv 1024
×6
Area 4
1 × 1 conv 512
3 × 3 conv 512
1 × 1 conv 2048
×3
Ave. pool
Judging object class
fc 1000
Neuron 675 (“magpie”) is most activated

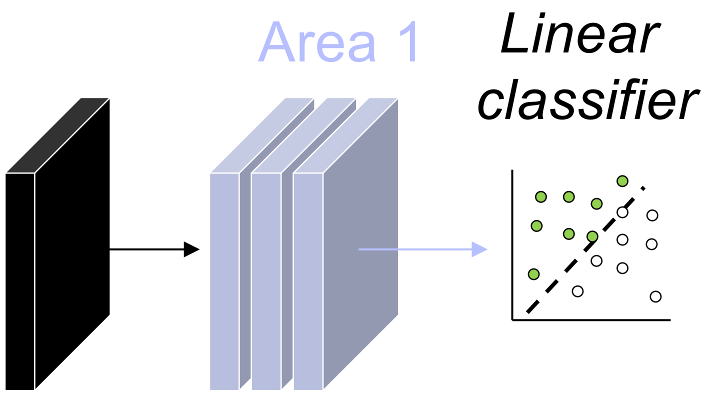

ResNet 50
Training set
1,188 everyday objects
× 10 random rotations
·Classifier was trained on "odd-one-out" task
·1 epoch (1,188 shapes), 30 epochs in total
Randomly assigned color
Area 1
Area 2
Area 3
Area 4
Linear classifier
7 × 7 conv 64
Max pool
1 × 1 conv 64
3 × 3 conv 64
1 × 1 conv 256
1 × 1 conv 128
3 × 3 conv 128
1 × 1 conv 512
1 × 1 conv 256
3 × 3 conv 256
1 × 1 conv 1024
1 × 1 conv 512
3 × 3 conv 512
1 × 1 conv 2048
Ave. pool
×3
×4
×6
×3
Freeze the learned weights (no training)
Train for chromatic discrimination task



0.4
CNN
S–(L+M)
CNN
-0.4
L-M
Area 1
Area 2
Area 3
Area 4
Linear classifier



Natural scene statistics may shape fundamental color vision functions.



Human-like asymmetry emerges in shallower layer

Color, objects and image segmentation

Gegenfurtner & Kiper, Annual Review of Neuroscience, 2003

WHY COLOR?

WHAT IS COLOR GOOD FOR?

IT‘S ALL ABOUT HUE

COLOR & OBJECTS: CHROMATIC EDGES

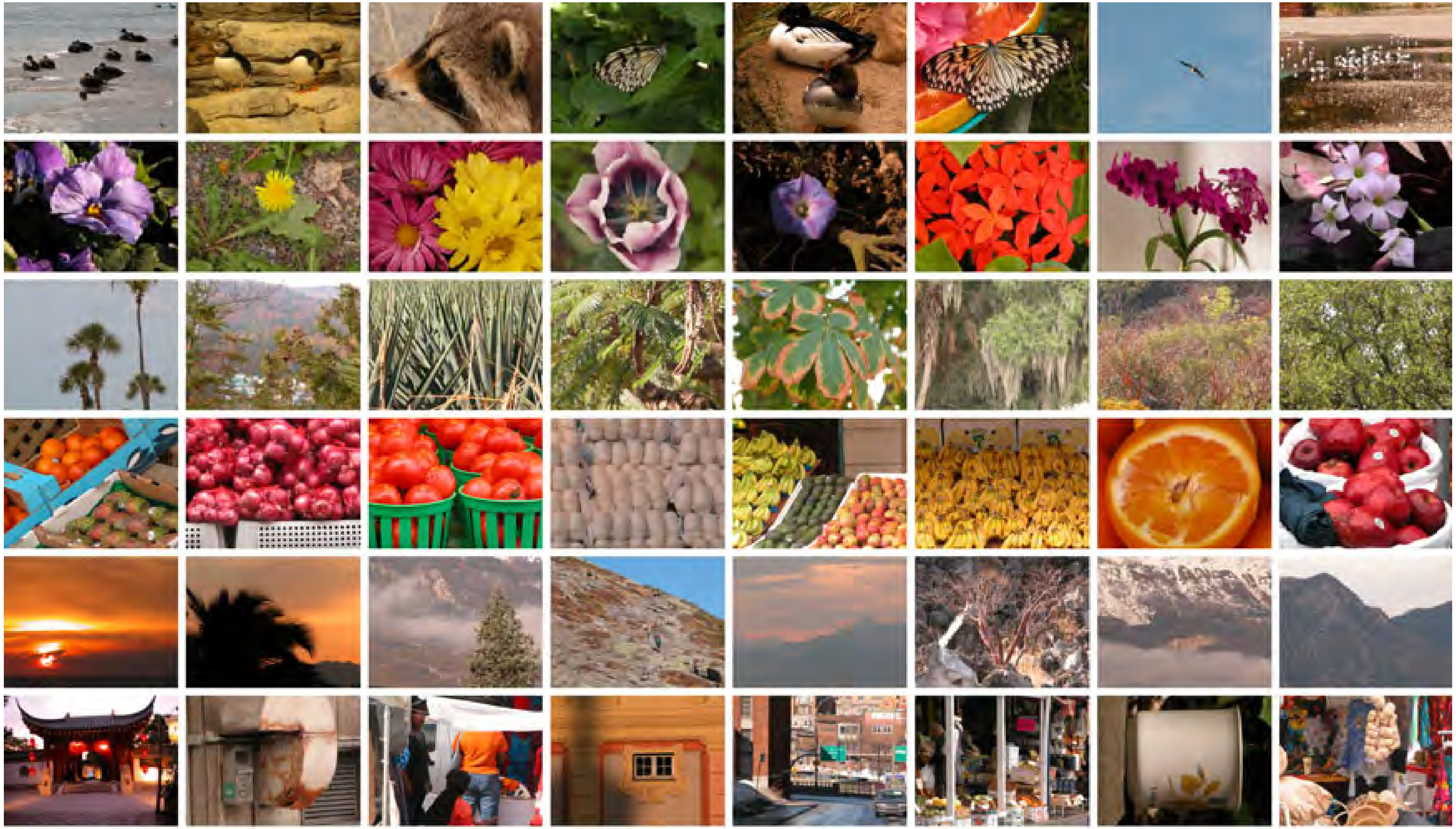
COLOR & OBJECTS: COLOR CONSTANCY

WHAT‘S NEXT?

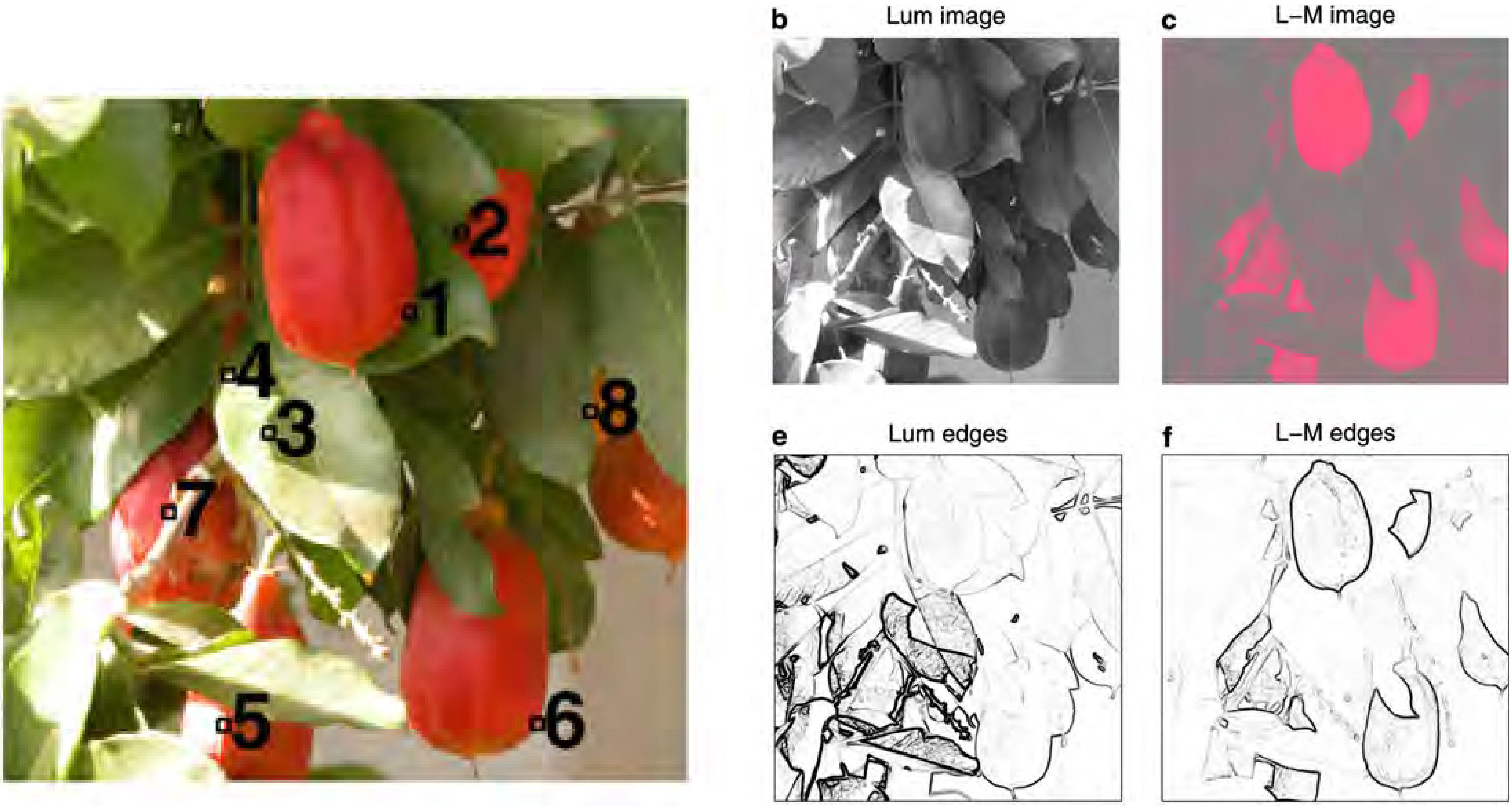
Color in natural scenes

http://tabby.vision.mcgill.ca

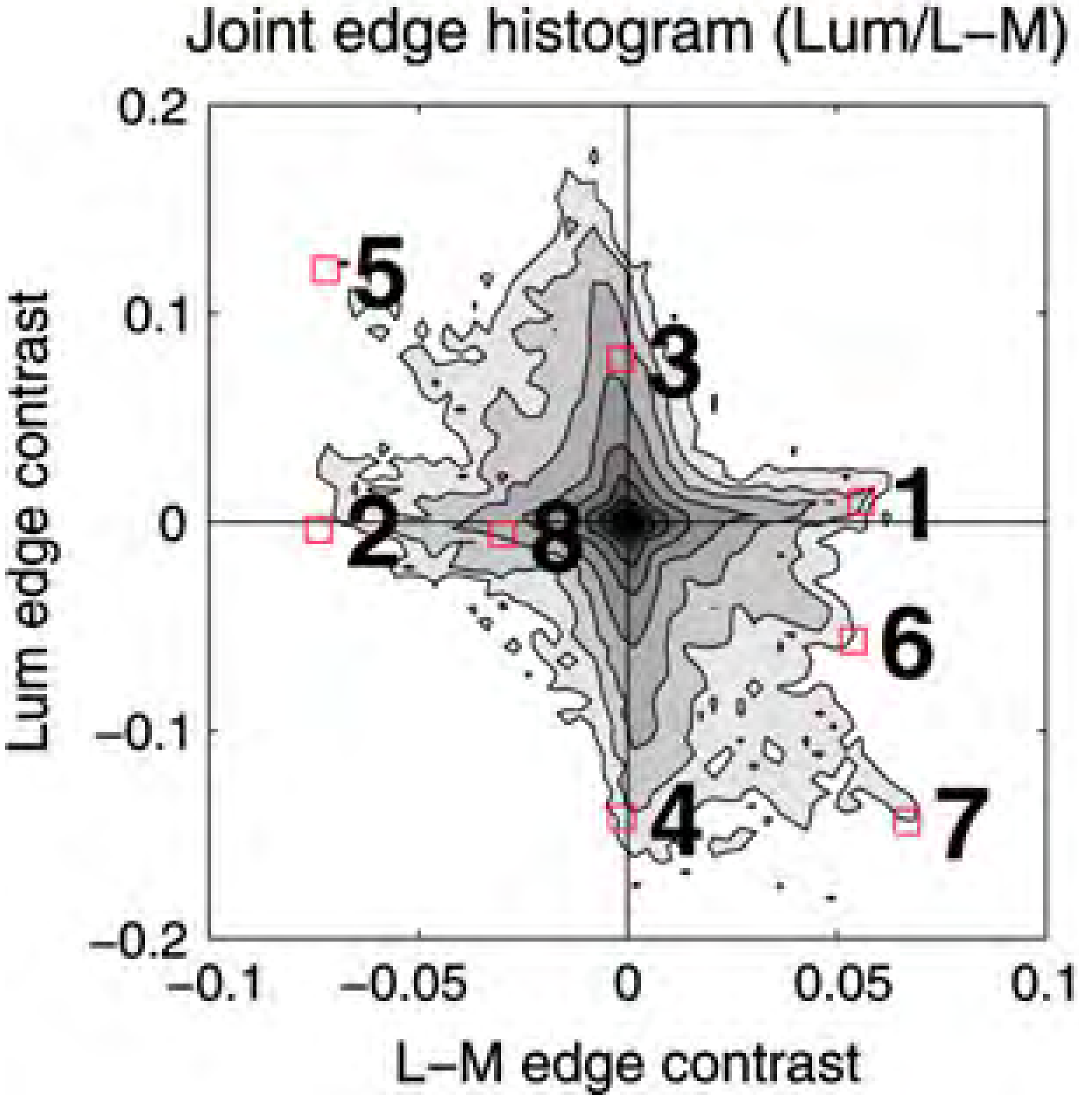
Color in natural scenes



http://tabby.vision.mcgill.ca

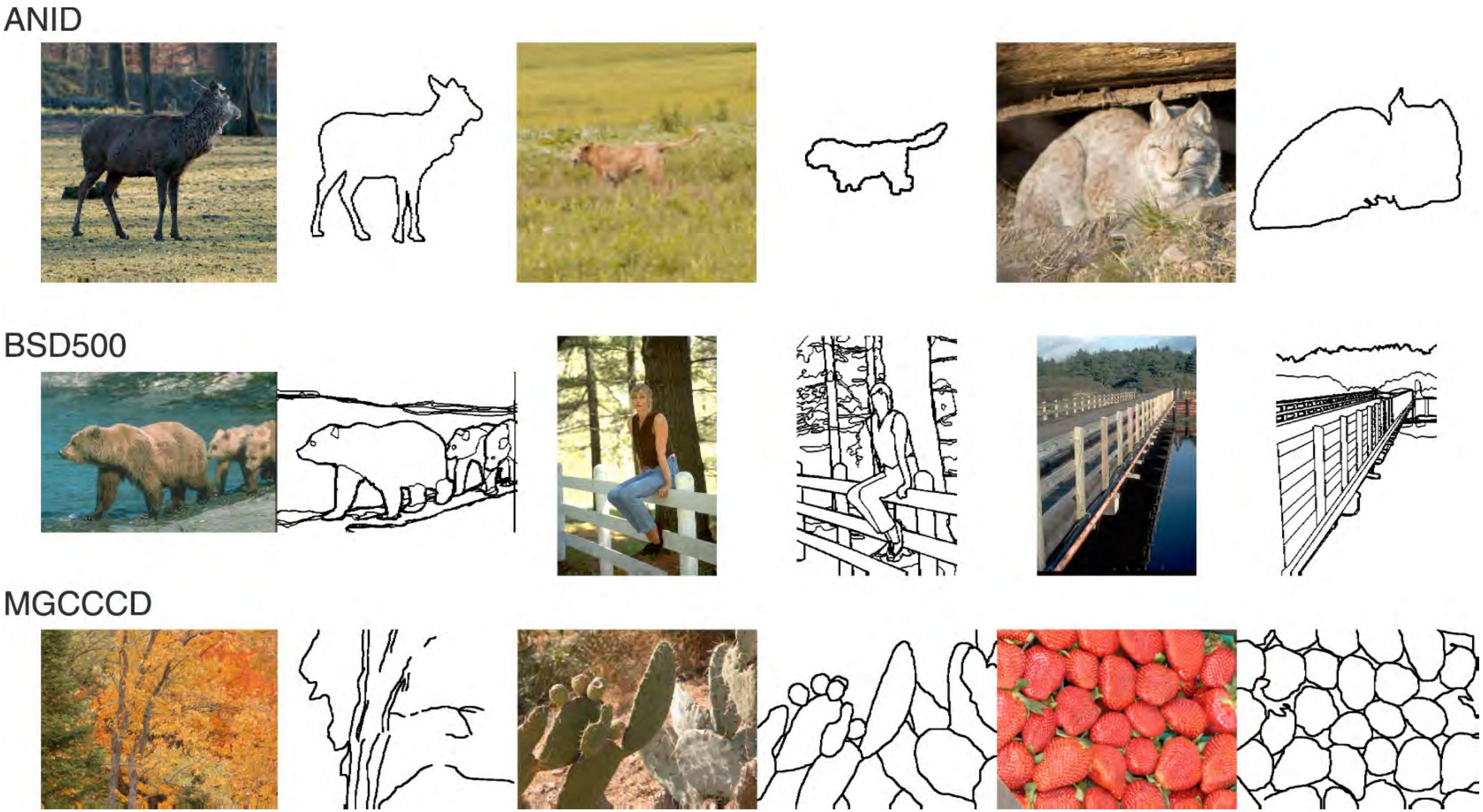


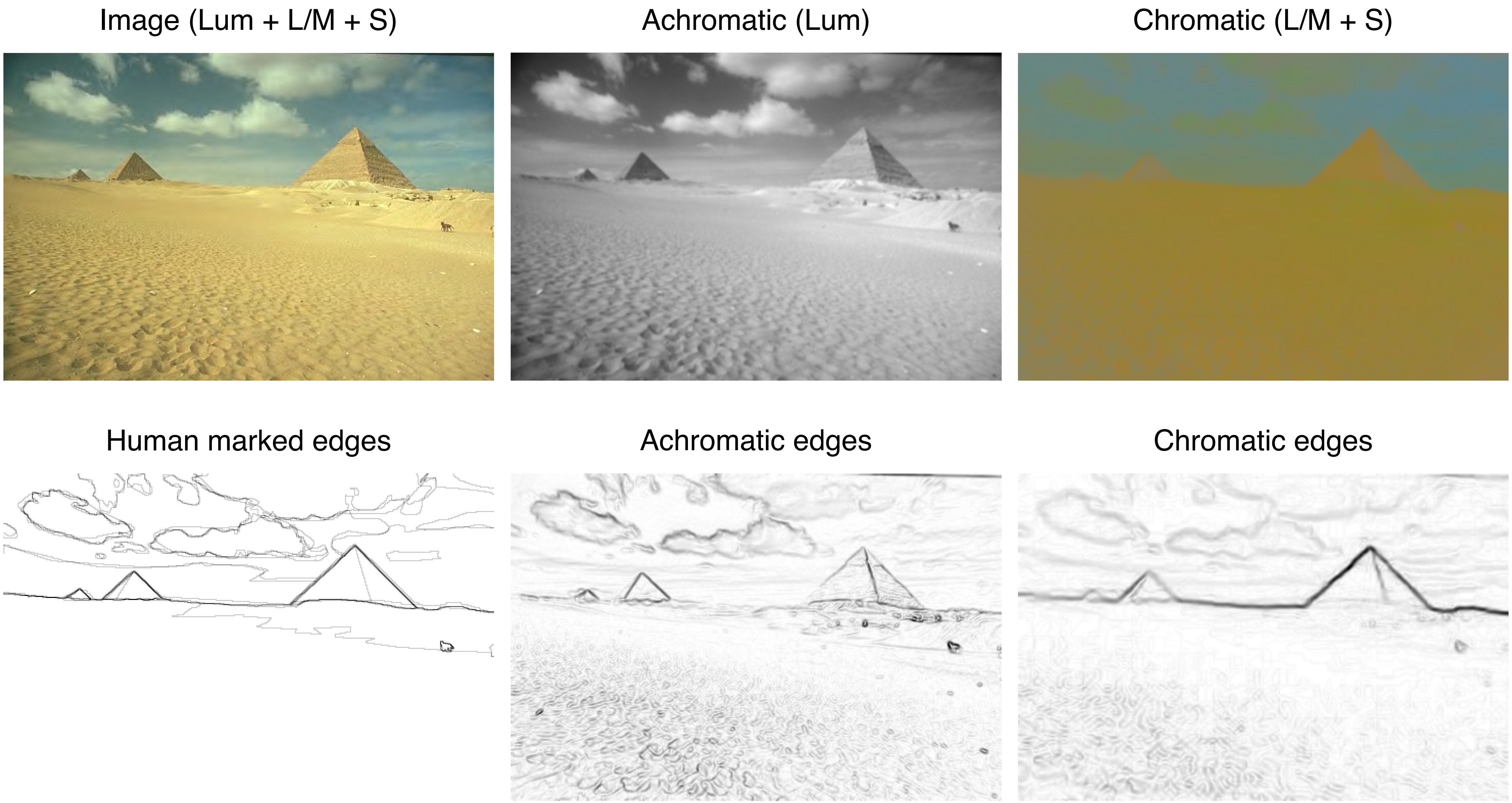
Hansen & Gegenfurtner, Visual Neuroscience, 2009



Hansen & Gegenfurtner, Visual Neuroscience, 2009

Human labeled edges

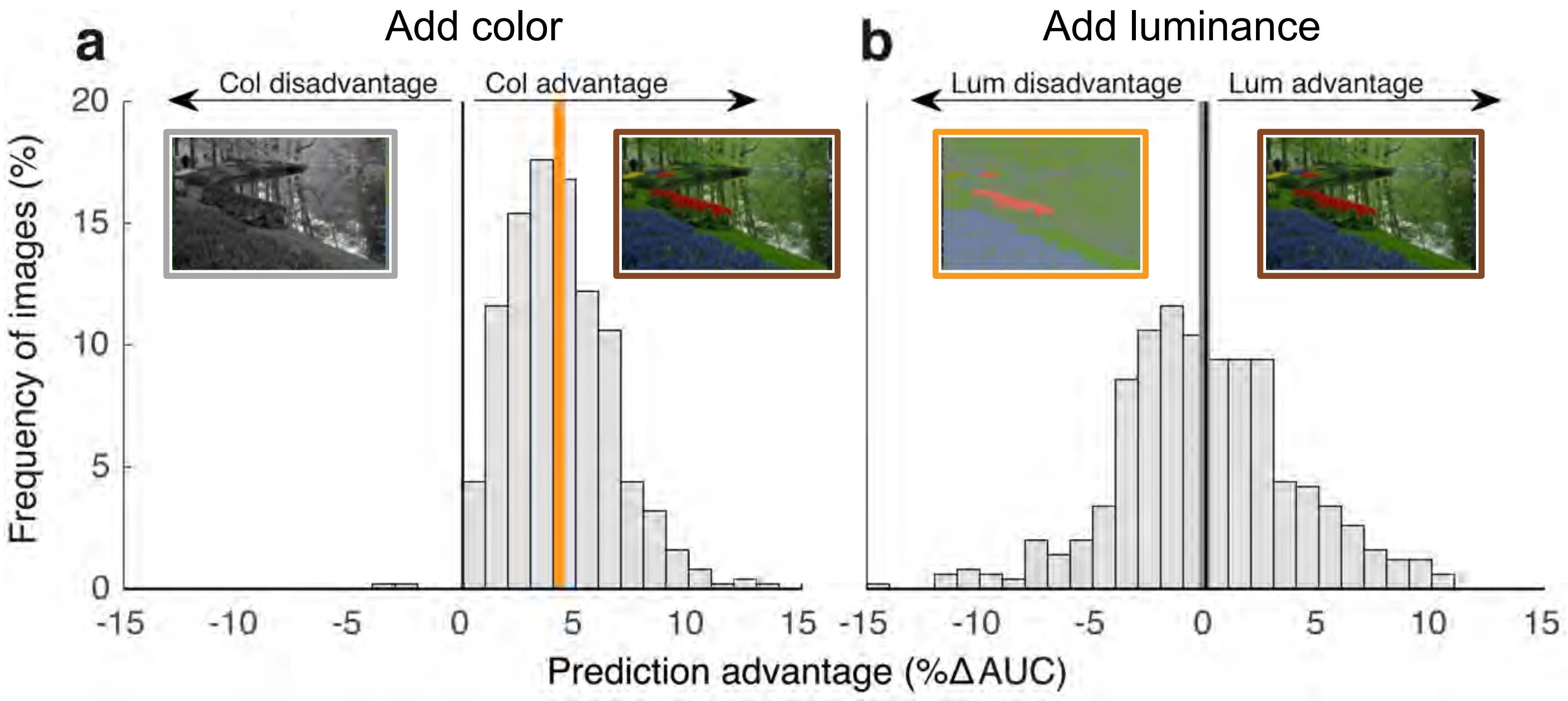




Hansen & Gegenfurtner, Journal of Vision, 2017

Color and luminance edges

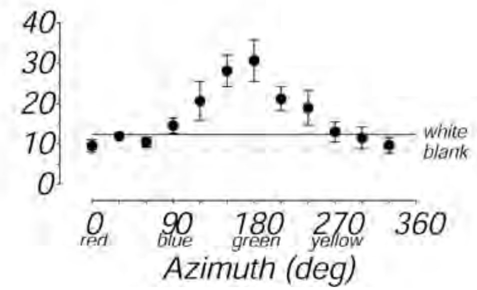
Color information better predicts human labeled edges

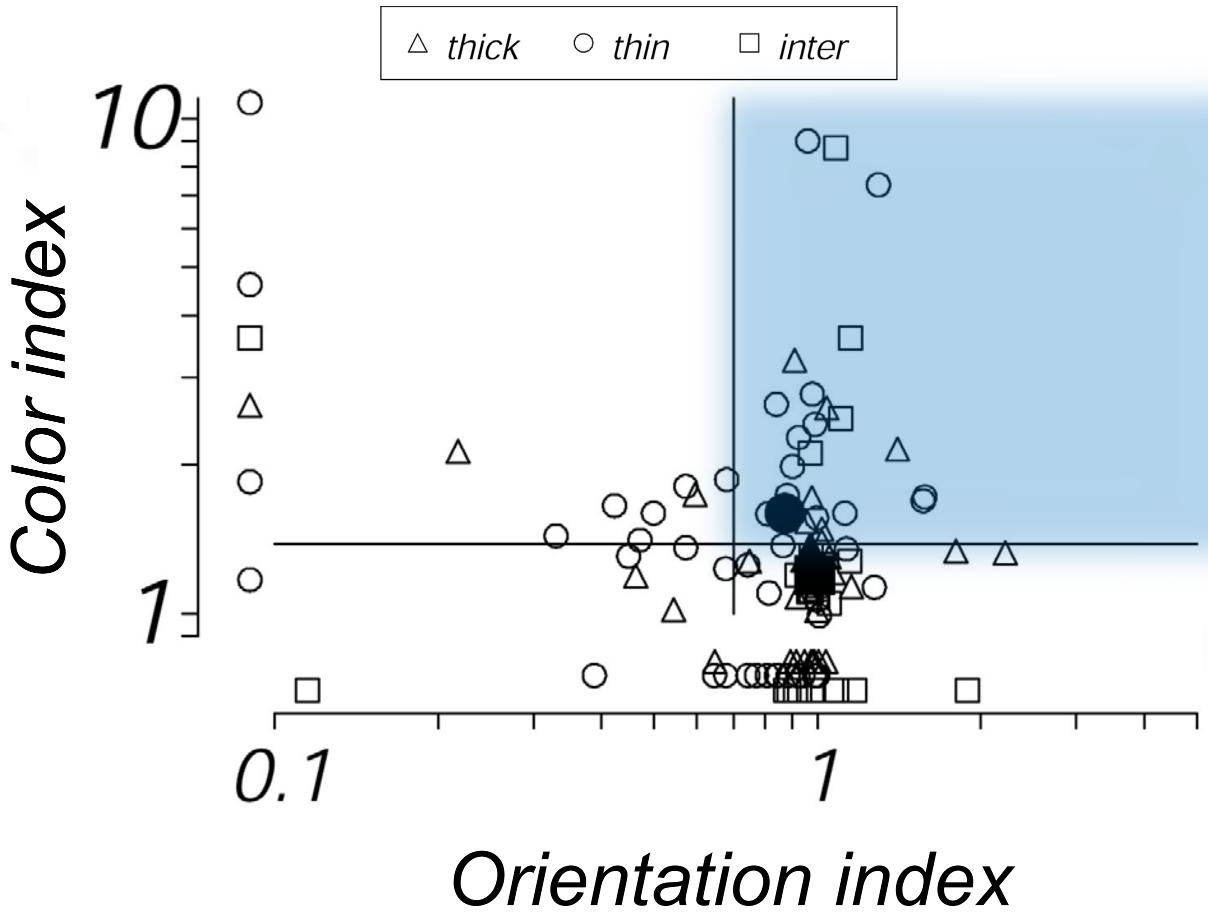


Hansen & Gegenfurtner, Journal of Vision, 2017

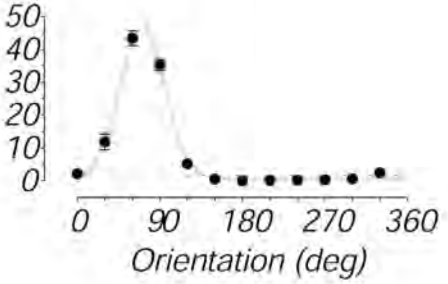
Selectivity for color and orientation

N = 57
V2





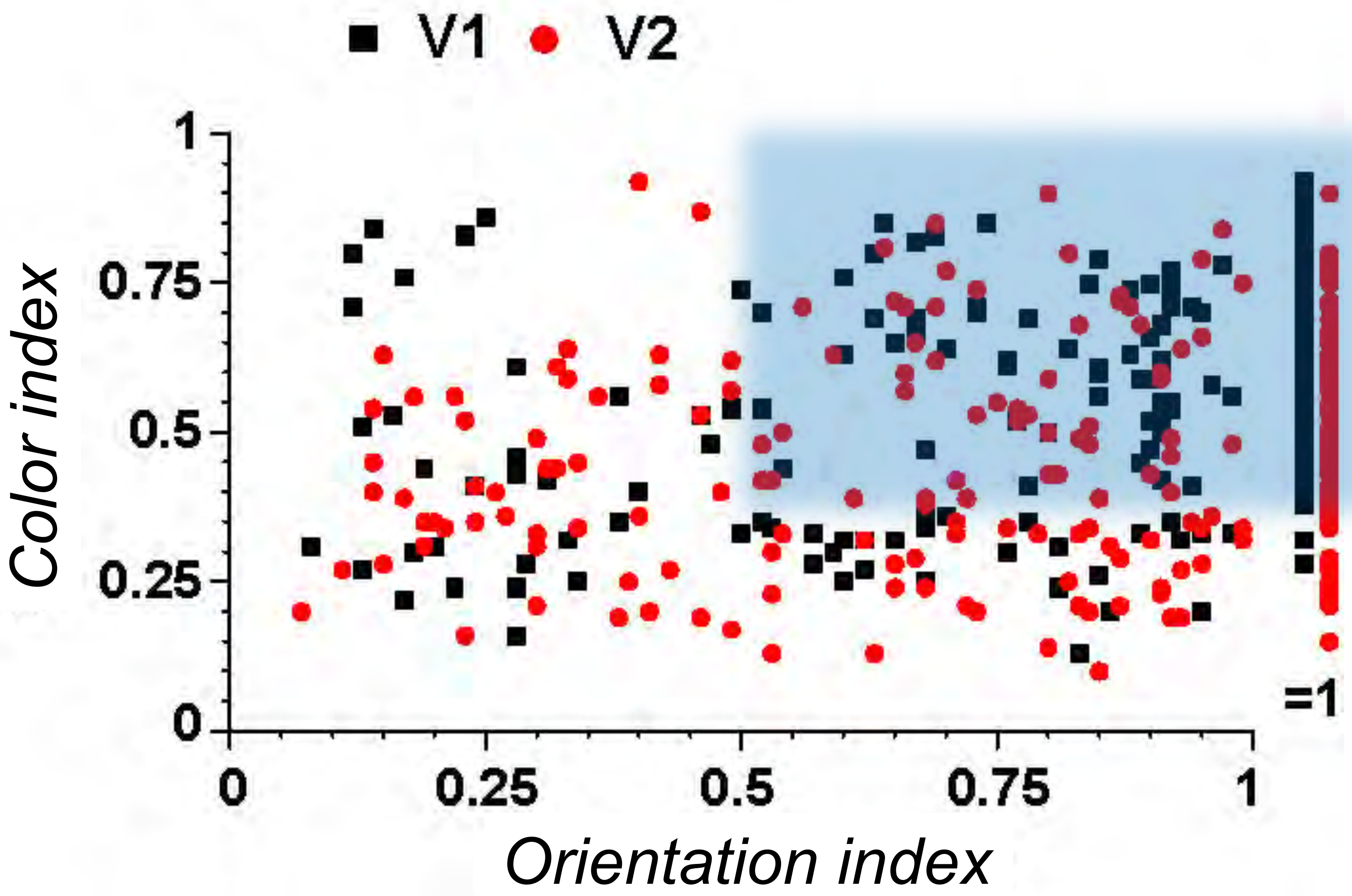
Cells selective for color and orientation



Gegenfurtner, Kiper & Fenstemaker, Visual Neuroscience,1996

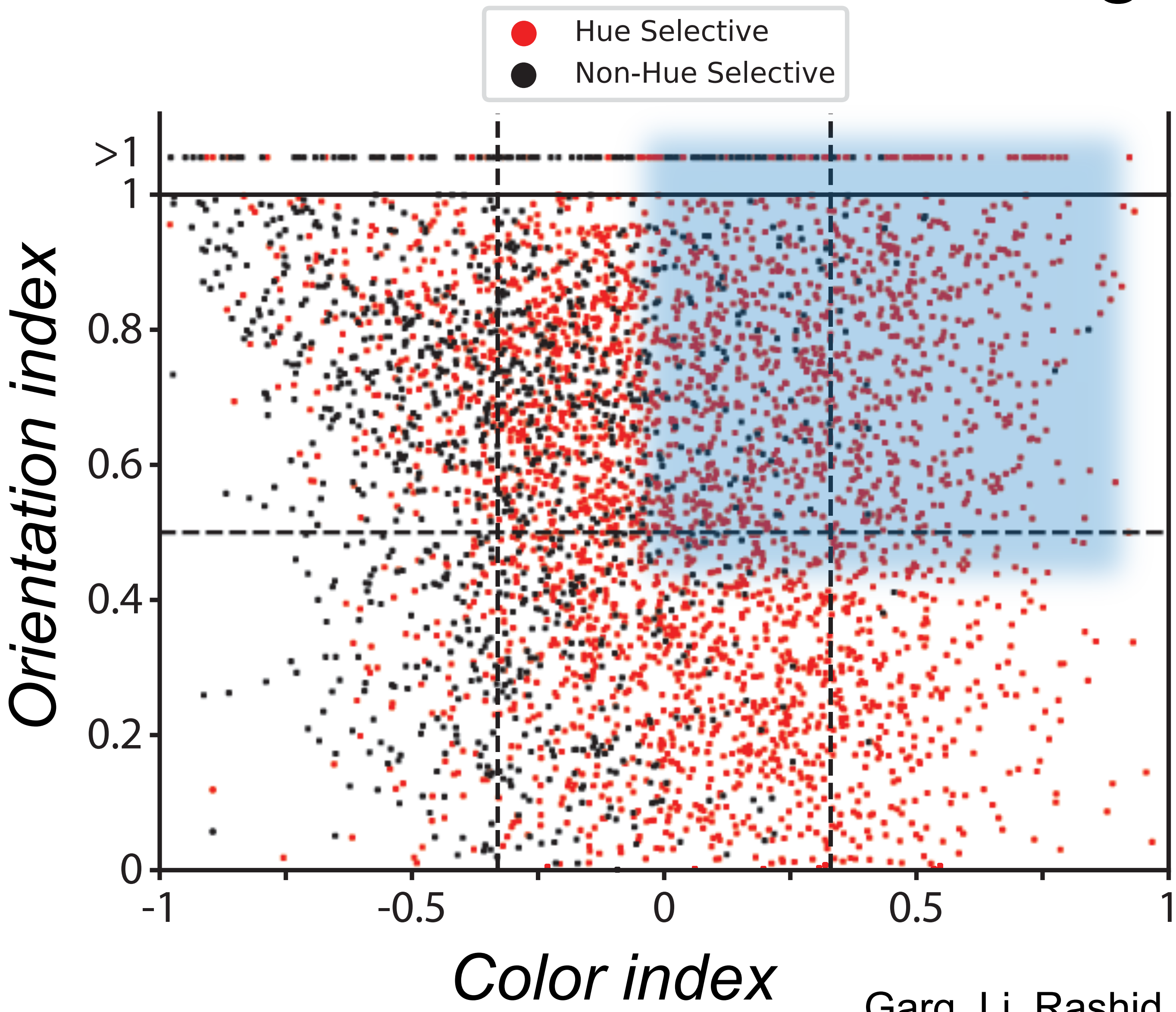
Color and orientation tuning

N = 187 (V1)
N = 233 (V2)



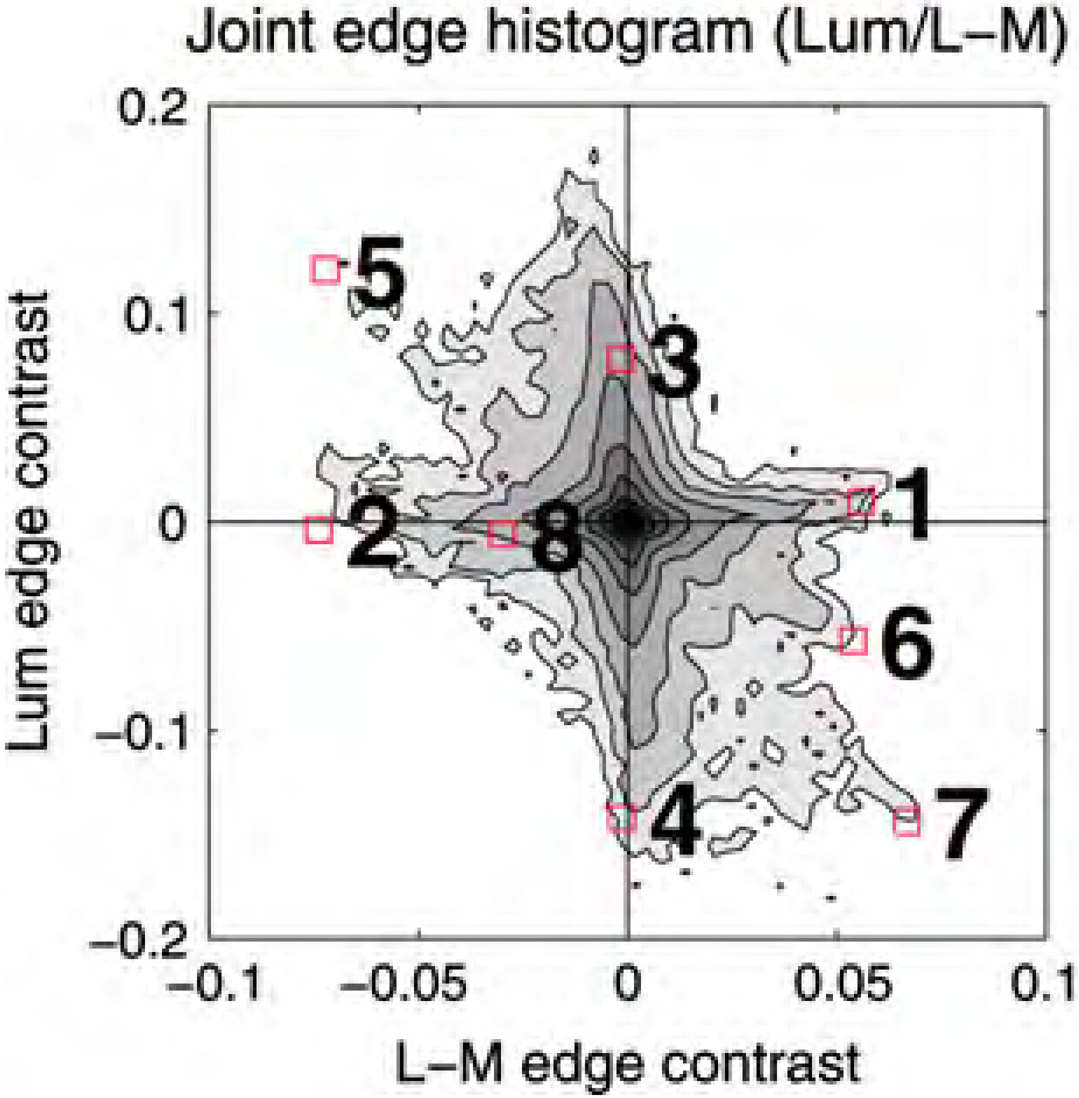
Friedman, Zhou & von der Heydt, Journal of Physiology, 2003

Color and orientation tuning



N = 4351
V1

Garg, Li, Rashid & Callaway, Science, 2019



Hansen & Gegenfurtner, Visual Neuroscience, 2009

WHY COLOR?

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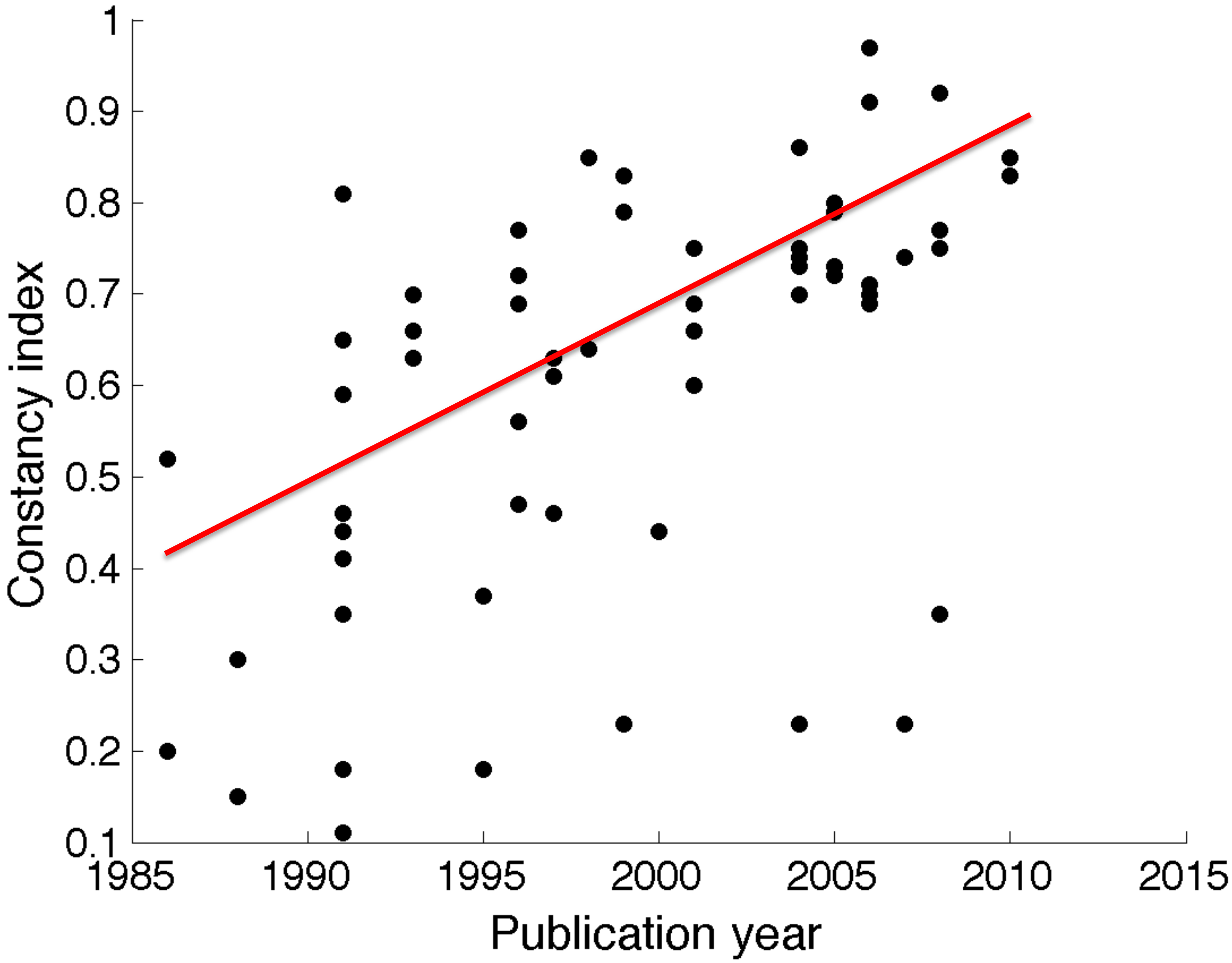
COLOR & OBJECTS: COLOR CONSTANCY

WHAT'S NEXT?

Orange

Grape

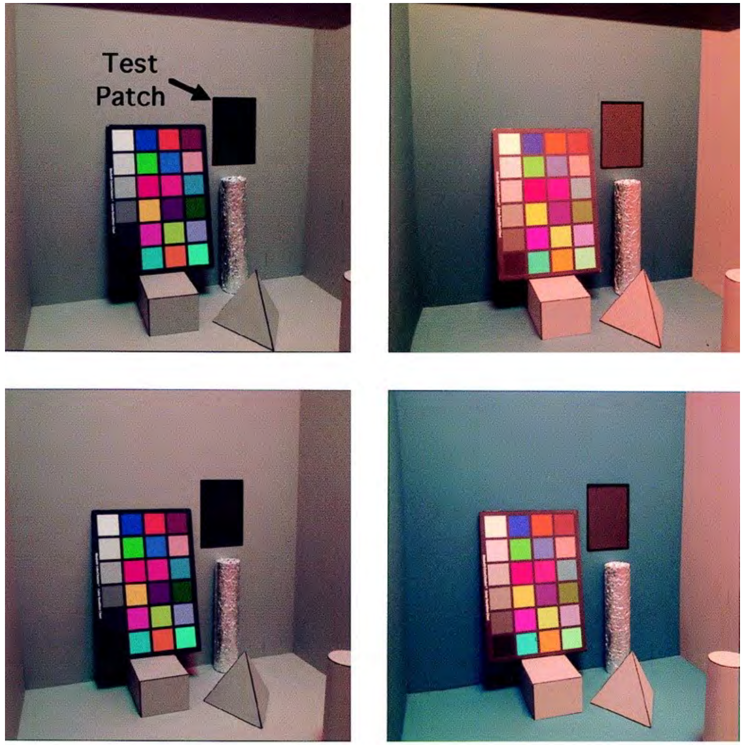
Witzel & Gegenfurtner, Annual Review of Vision Science, 2018



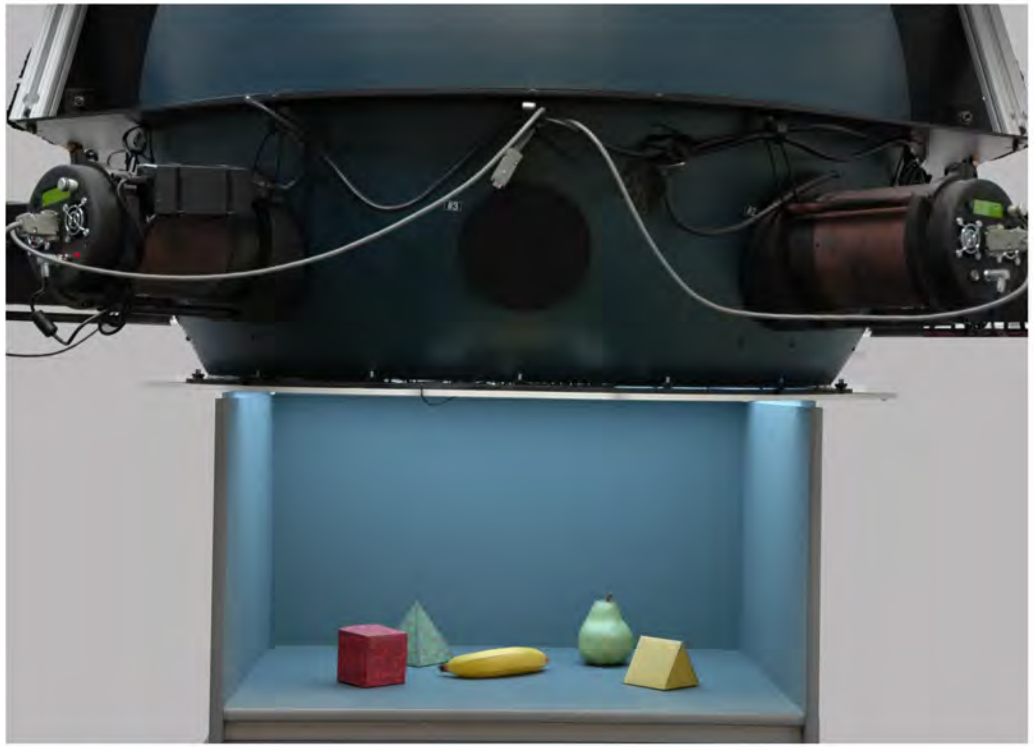
Witzel & Gegenfurtner, Annual Review Vision Science, 2018

Data after Foster, 2011

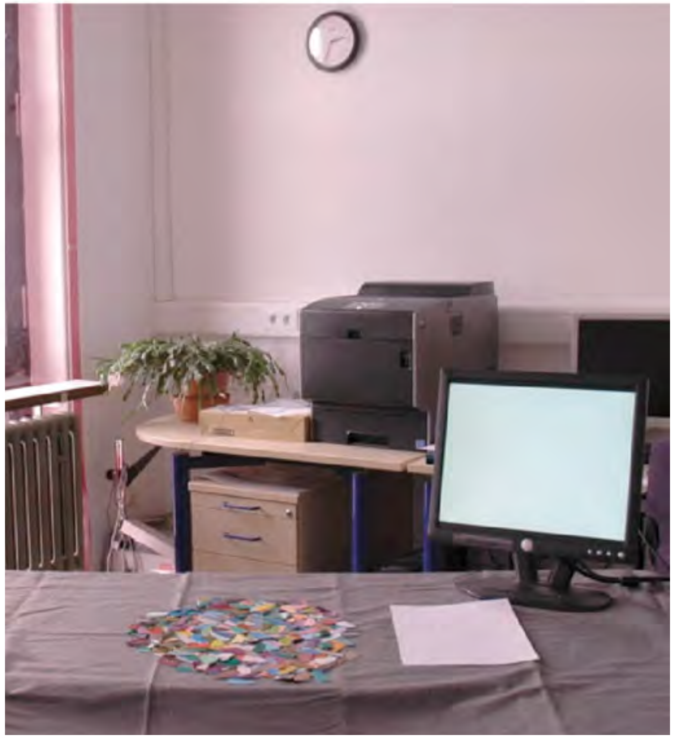
Real-world color constancy



Kraft & Brainard,
PNAS, 1999



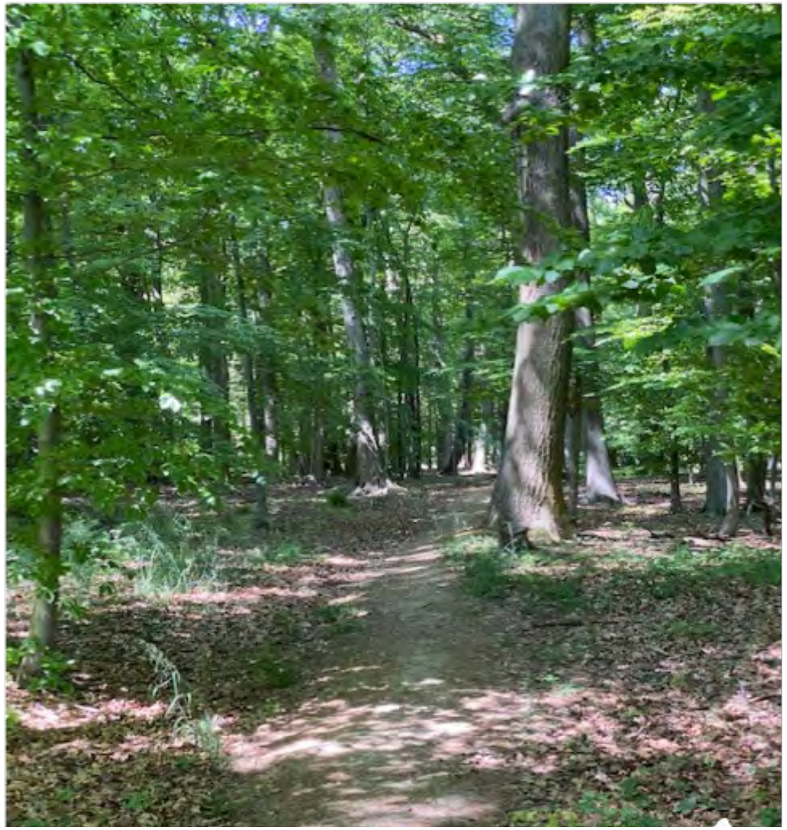
Pearce, Crichton, Mackiewicz, Finlayson & Hurlbert
PloS one, 2014.



Olkkonen, Hansen & Gegenfurtner,
J. Vision, 2009

Color constancy is high under real-world conditions, with a single uniform illuminant and a large field of view.

Virtual Reality 2022



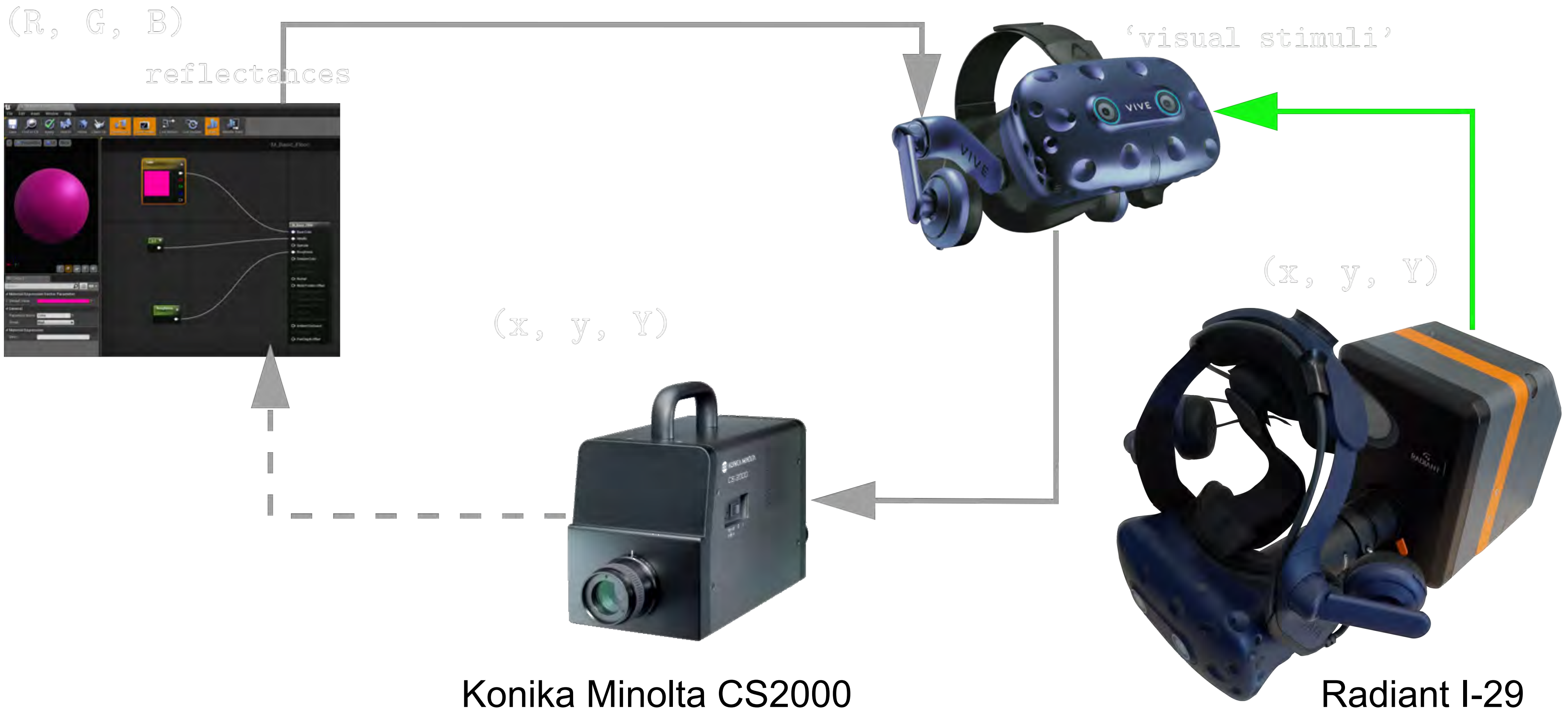
REAL

UNREAL ENGINE

VR color calibration

Rendering system

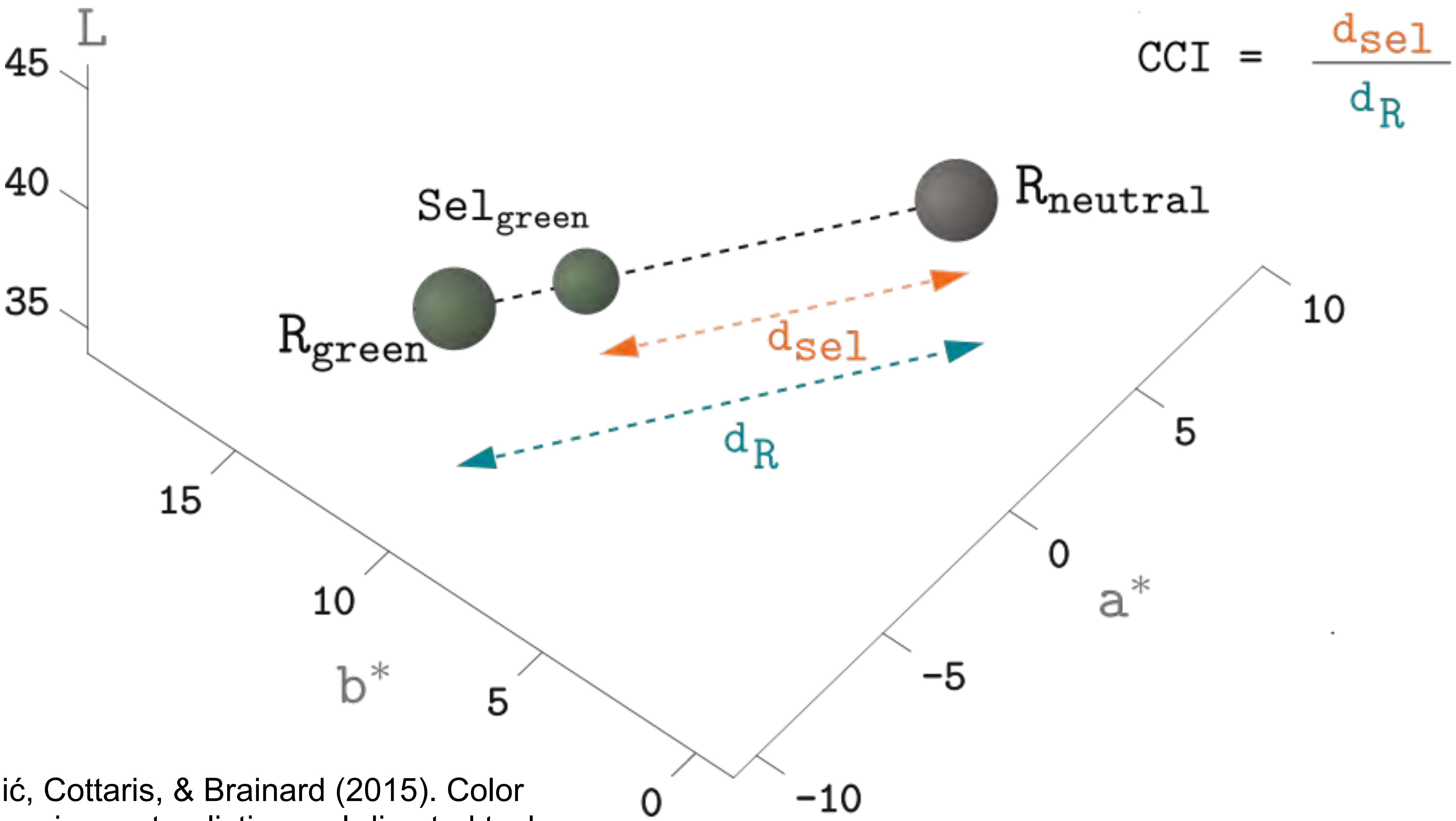
- OpenGL via Psychtoolbox
- UNREAL engine



Konika Minolta CS2000
Spectroradiometer

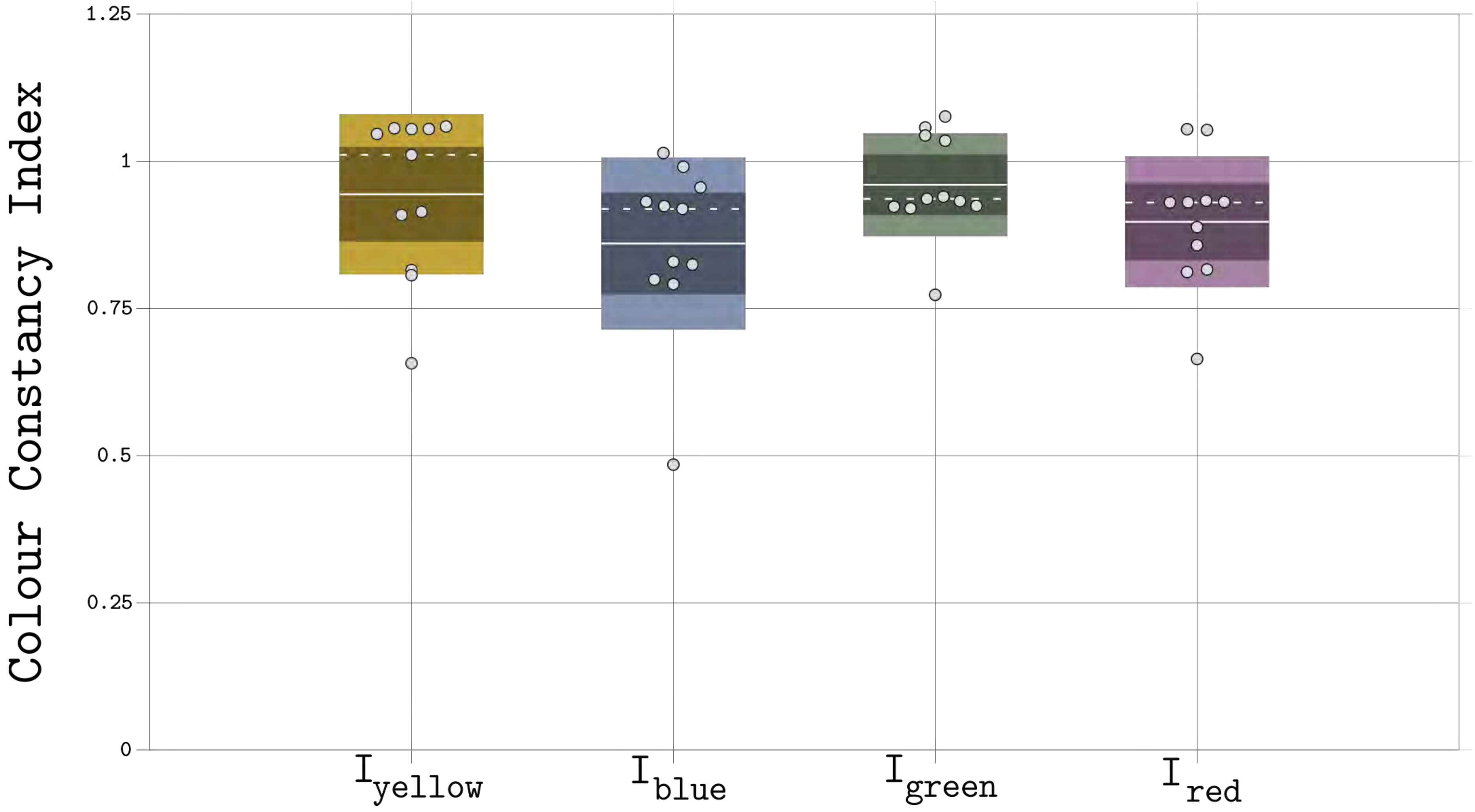
Radiant I-29
Colorimeter

Gil Rodríguez, Bayer, Toscani, Guarnera, Guarnera & Gegenfurtner, *SN Computer Science* (2022)



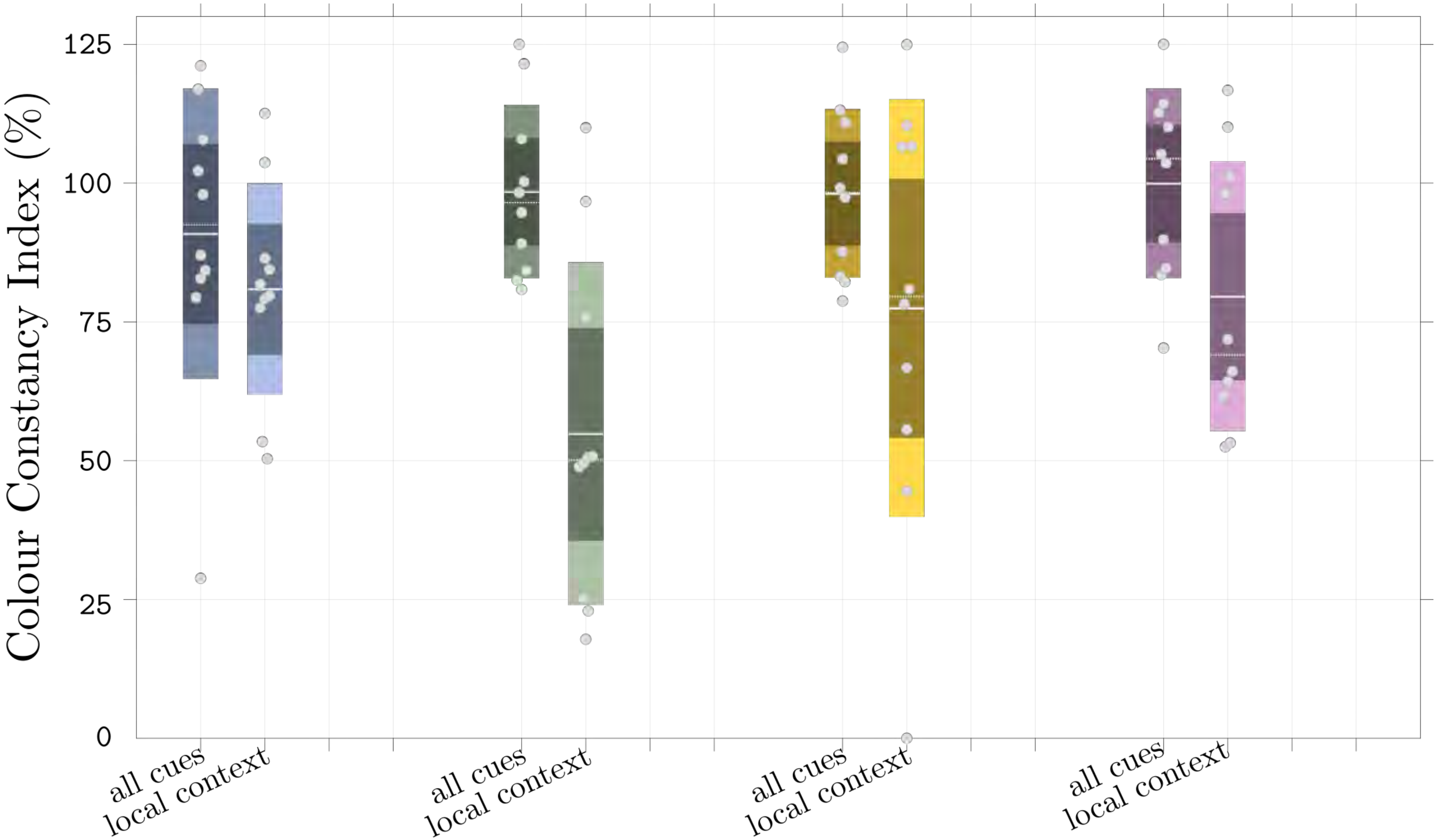
Radonjić, Cottaris, & Brainard (2015). Color constancy in a naturalistic, goal-directed task. *Journal of Vision*, *15*(13), 3-3.

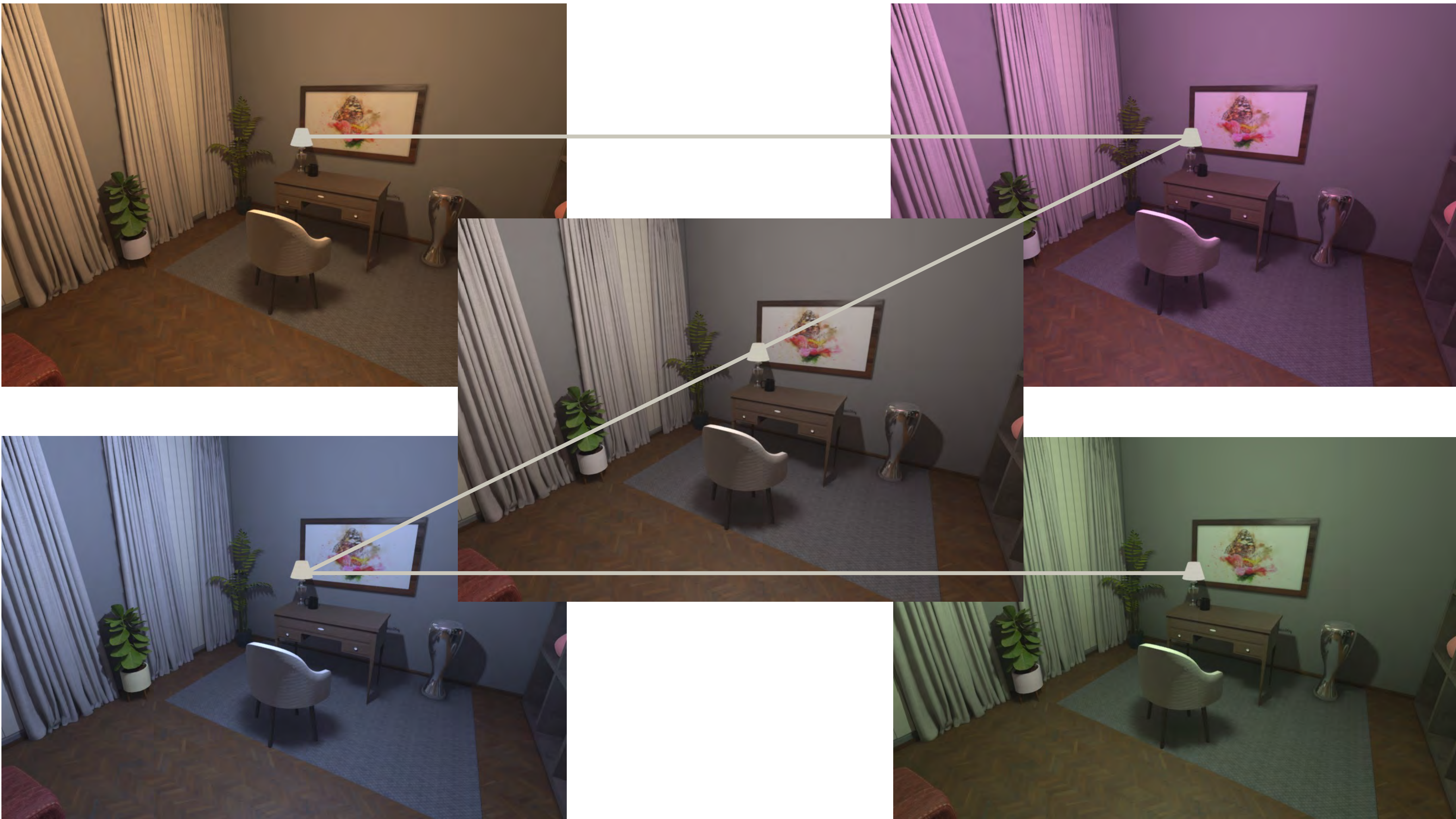
VR first results



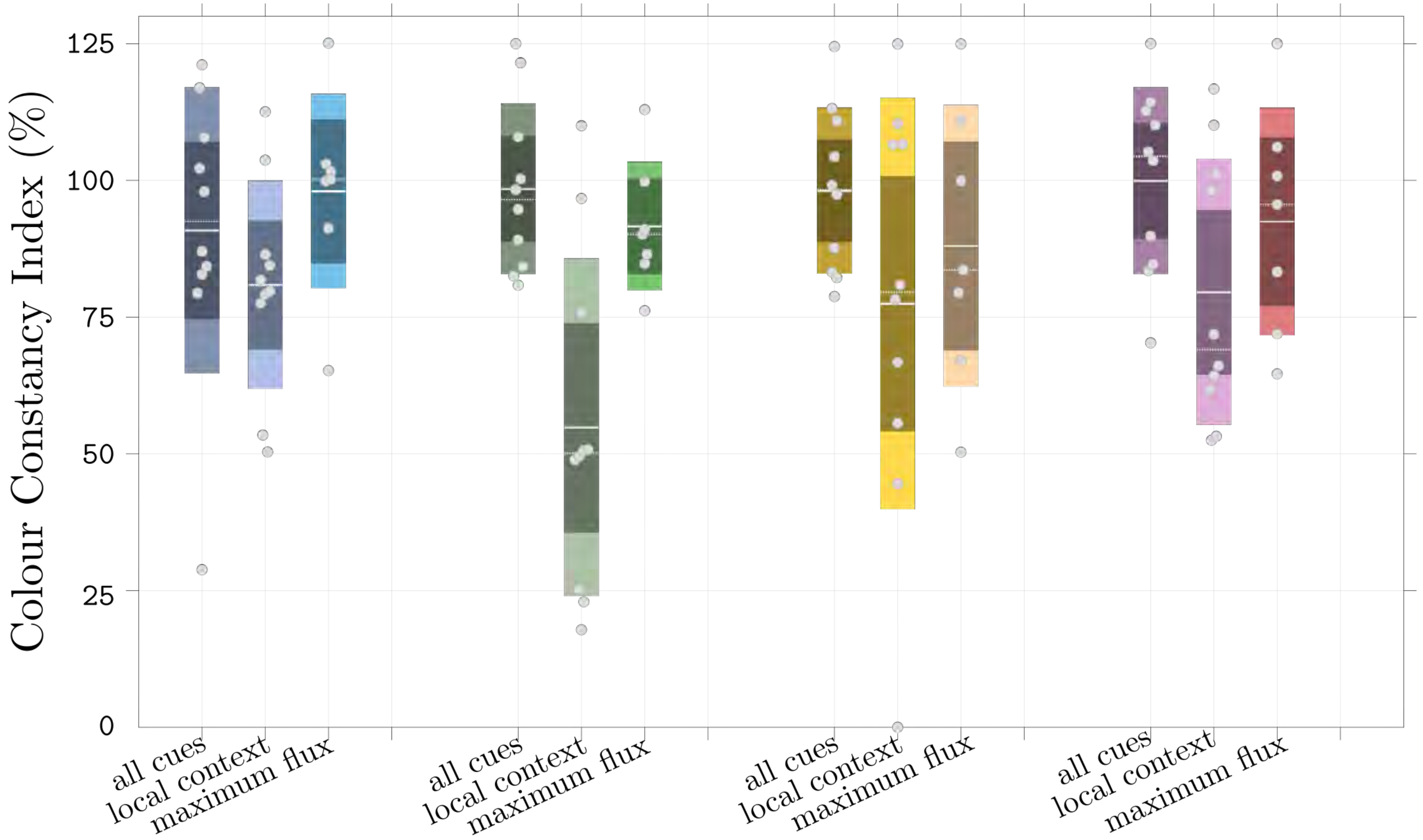
Gil Rodríguez, Bayer, Toscani, Guarnera, Guarnera & Gegenfurtner, *SN Computer Science* (2022)

Role of local context

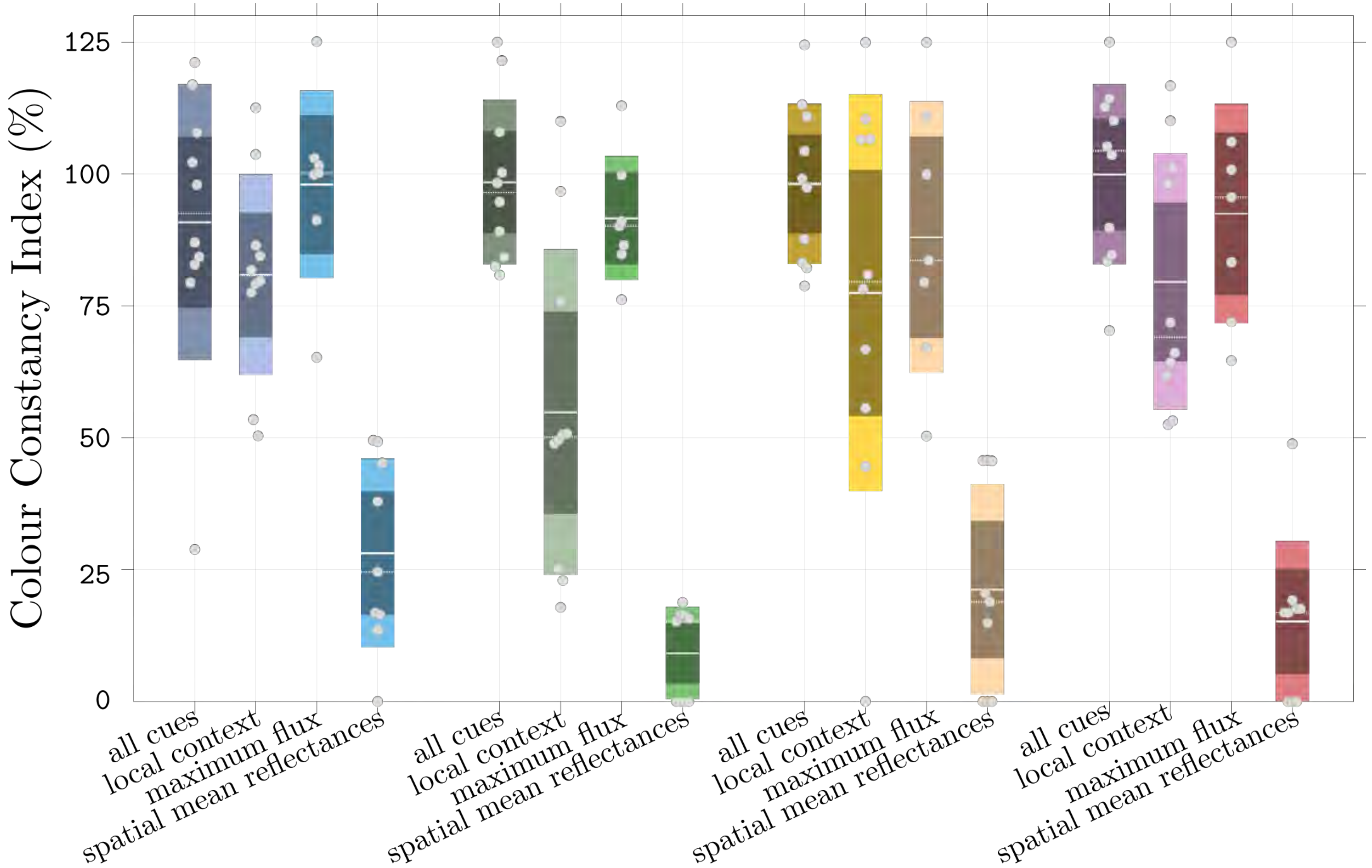




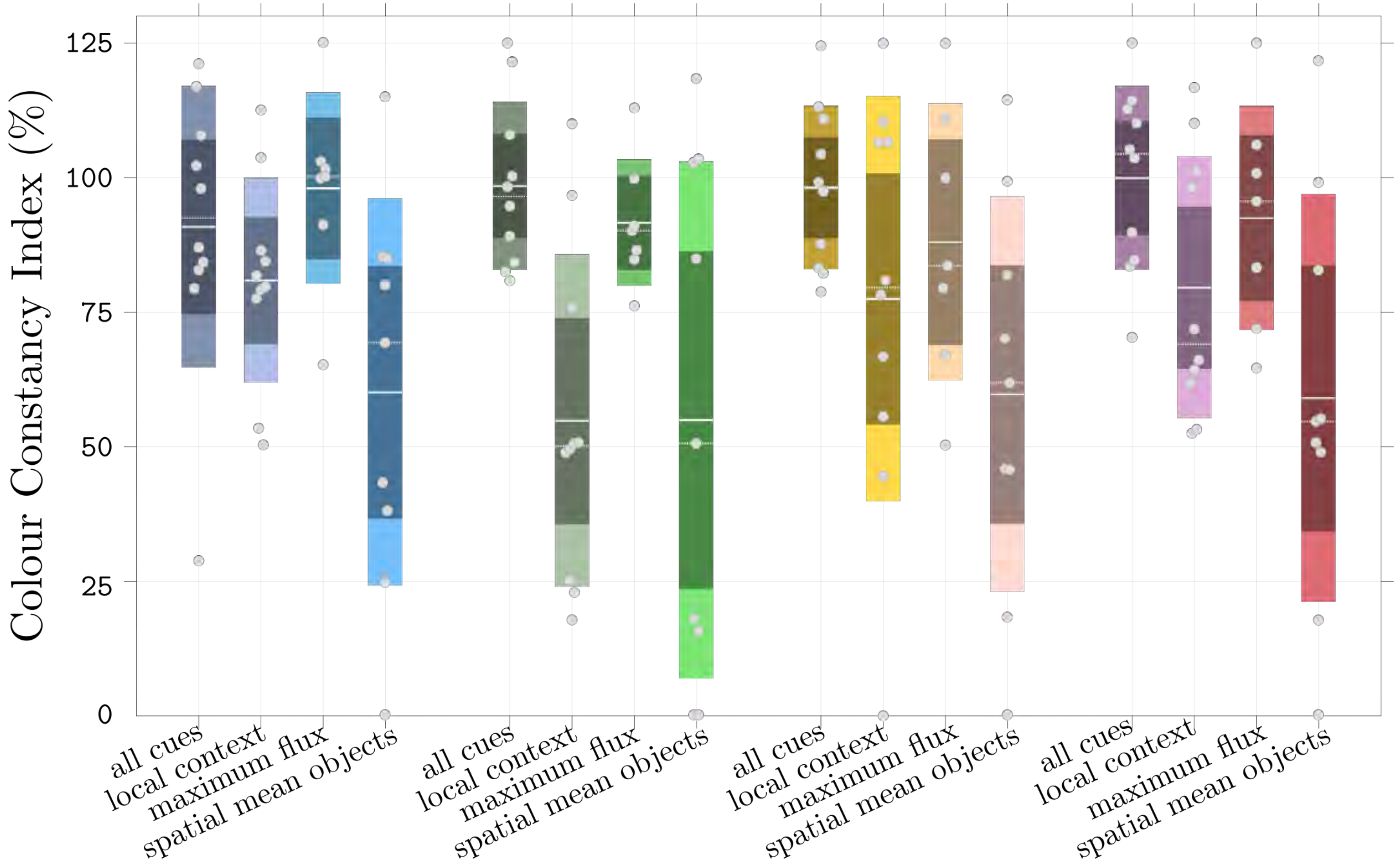
Role of brightest object



Role of average color

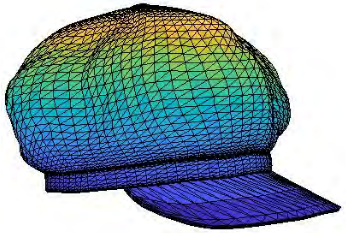


Role of average color

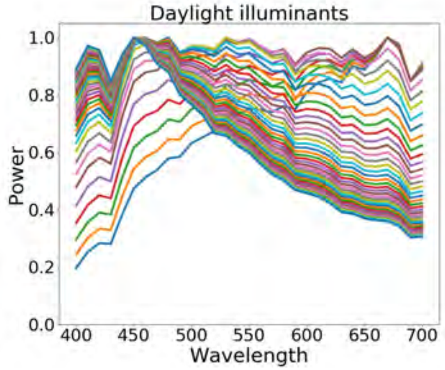


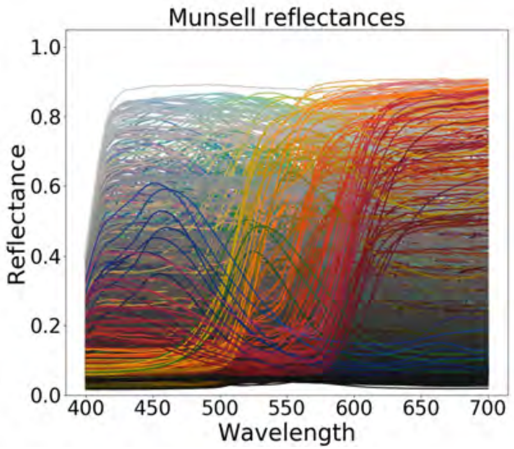
DNN for color constancy

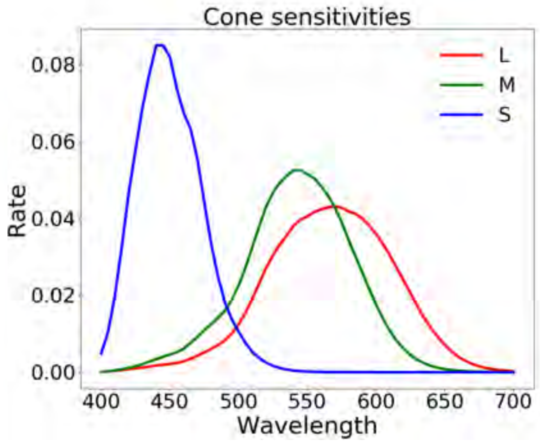
- 2115 3D shapes



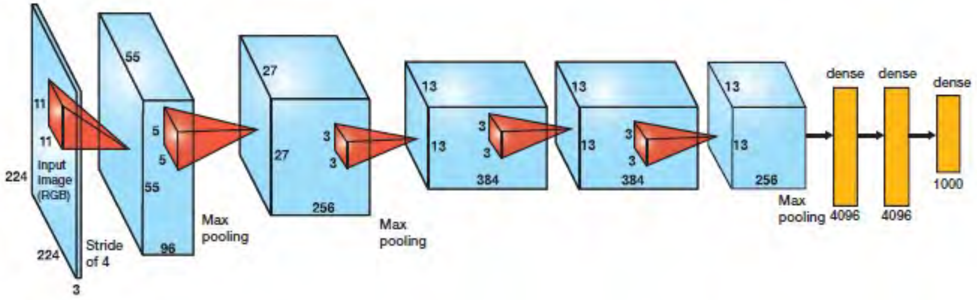
- 330 Munsell reflectances (WCS)
- 265 daylight and forest illuminants





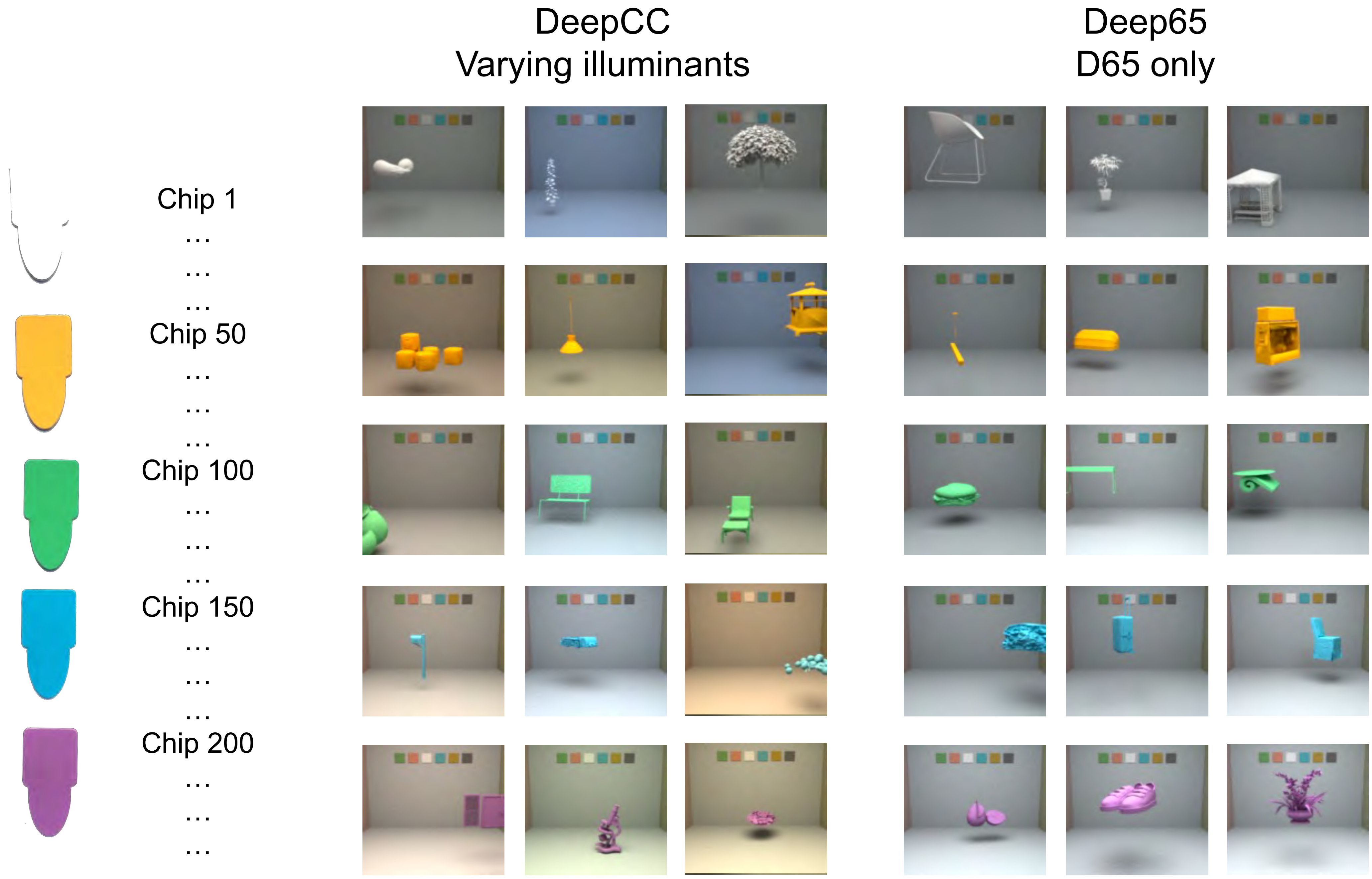


- Stockman & Sharpe cone fundamentals
- Mitsuba spectral rendering

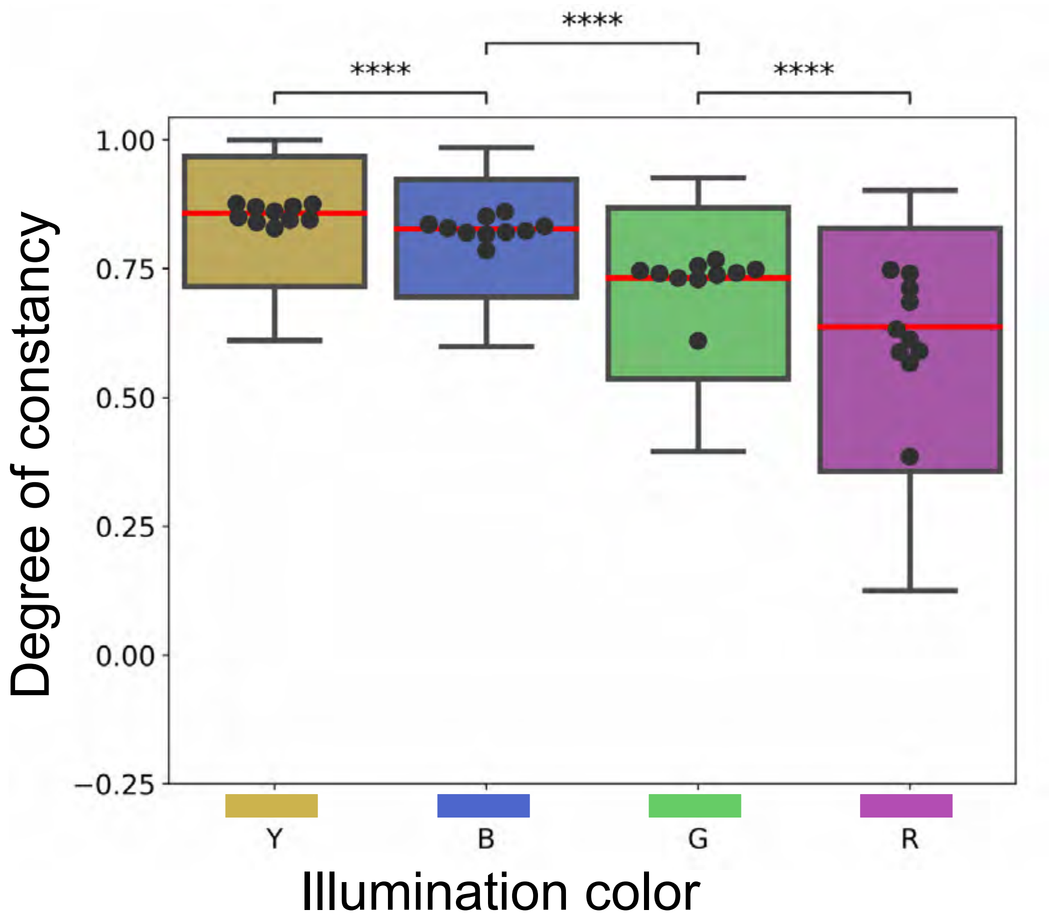


- 181.500 (330 x 550) cone excitation images (124 x 124 pixel)

Flachot, Akbarinia, Schuett, Fleming, Wichmann & Gegenfurtner, Journal of Vision, 2022


DeepCC
Varying illuminants
Deep65
D65 only
Chip 1
Chip 50
Chip 100
Chip 150
Chip 200

DNN for color constancy



A DNN (DeepCC) can achieve close-to-perfect color constancy using naturalistic input stimuli

Color constancy gradually increases throughout the network layers

DeepCC evolves a human-like representation of hue, chroma and lightness

Every single network node is available for further analysis and can be compared to neurophysiological data

Color vision: from pixels to objects

- **Classic color vision**
  - Defined by 3 color coordinates
  - No direct relationship to real-world objects
- **Objects**
  - Defined by distributions in color space
  - Hue is the major invariant, important for segmentation and memory
  - Lightness and saturation derived from distributions
- **Natural scenes**
  - Feasible in VR, DNNs (and neuroimaging: MEG, fMRI, 2pi)

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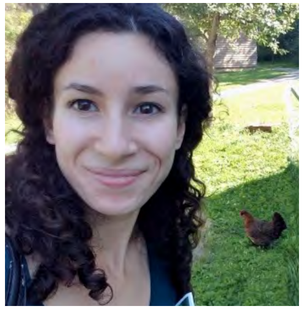

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Thanks!